Bipolar Disorder Predictive Model: A Study to Analyze and Predict Emotional Change Using Physiological Signals

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Dedication

I dedicate this thesis to my parents, Zainab and Anwar Hashim, and all my siblings- who took care of me and everything for me. I also dedicate this thesis to Dr. Arshia Khan, who has been an advisor, counsellor, friend and encouragement in every step of the way.

Abstract

Bipolar disorder, a chronic mental illness, most common among people of ages 18 years and older, affects over 2.6 percent of the United States population alone. Although this illness cannot be cured, it can be managed by continuous tracking and monitoring. Hence, if a manic or depressive episode can be identified or predicted in its early stages, severe damage can be minimized, if not prevented.

This thesis proposes the design of an objective sensor based system that is based on physiological predictors for the continuous and autonomous monitoring of bipolar patients. This system consists of a pulse rate sensor to record heart rate, and an electrodermal activity sensor to trace the emotional and cognitive state changes and does not rely completely on self-assessment or reporting. Furthermore, it investigates how psychological changes affect physiological responses, such as Heart rate variability (HRV) and Electrodermal activity (EDA). We conducted a study with 50 healthy participants, where each participant was subjected to a certain degree of image and audio induced emotion. Baseline and the emotional stimuli data was collected. Time-domain and non-linear analysis of HRV was then performed on the collected HRV data. In addition, EDA data analysis was performed by decomposing it into tonic and phasic components.

We investigated the ability of HRV and EDA to identify the activity of the autonomic nervous system in response to emotional stimuli. Moreover, the extracted features from the data were then used to build machine learning models to predict the given psychological change in response to the emotional stimuli. Our results showed that these combination of HRV and EDA features from the study we conducted yielded an average accuracy of up to 73% with Support vector machine, and 68.3% with Discriminant analysis for predicting emotional change in healthy individuals.

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1 Introduction

Bipolar disorder is one of the world's 10 most incapacitating disorders [35]. Bipolar patients are at a high risk of suicide, 20 to 25% of individuals suffering with Bipolar Disorder make suicidal attempts at least once in their lifetime [43]. Currently there is no known cure for this illness, and pharmacotherapy and psychotherapy are the only treatments that can help minimize the damage, effects and intensity of a bipolar manic or depressive state. Continuous monitoring and tracking of emotional state are pivotal for bipolar patients. Especially in severe depressive state, the patients find themselves functionally impaired, and not only their social but their professional life is severely affected. Not only that but 93% of the caregivers also have reported moderate to extreme anxiety and distress while living with a bipolar patient [62].

The hypothesis of this work is that a multi-parametric autonomous sensor fusion based predictive model based on heart rate variability and Electrodermal activity , can help predict and identify manic and depressive episodes in patients suffering from bipolar disorder.

Bipolar patients entail continuous treatments, both inpatient and outpatient, inflicting an annual cost of more than $150 billion [62]. These large numbers have raised a serious concern, prompting the prioritization of researches on an alternate effective health care solution. Although Bipolar disorder cannot be cured, it can be managed by continuous tracking and monitoring. Hence, if the manic or depressive episode can be identified or predicted before its onset in its early stages, severe damage can be minimized, if not prevented. The therapeutic effect of medications and therapies

is most effective when given at early stages of depression or manic episodes.

The emotional dysregulation, ascertained using heart rate variability and Electrodermal activity, and the disrupted sleep patterns, are the primary bio-markers that have the potential to predict bipolar episodes [22][66][45]. Up till now the diagnosis is entirely based on the feedback of the patient and the psychiatrists understanding of it, both of which are subjective, using sensor based physical data collecting can help overcome this gap.

The most creative aspect of this proposed system is that It is a hybrid of two different sensor based predictive models and mobile application. The use of two different sensory data diversifies the approach and encourages us to aim for a more accurate prediction model. In addition, the nature of the mobile application provides ease of viewing, alert management, and self-reporting. The feasibility, usability, and constant connectivity of mobile devices, has promoted the progressive use of mobile devices to aid in tracking, monitoring and managing depression, bipolar disorder, sleep disorder and many other mental health and other illnesses.

There are potentially transformative aspects of the proposed work, it contributes to the research work currently done in assistive technologies to improve the quality of life of individual diagnosed with Bipolar Disorder. Prediction of the manic/depressive episode can help develop protocols and mechanism to prevent these episodes. Also, sensor-based monitoring will give us a better understanding of the physiological changes that potentially promote and encourage mania/depression.

For the said purpose, we set up a mobile device to collect Heart rate variability and Skin conductance to collect data for our predictive model. We conducted a study on campus with 50 healthy participants between the age of 18 and 30, to investigate how psychological changes affect physiological responses. This user study deals only with healthy participants to investigate the ability of EDA and HRV to identify the

activity of the autonomic nervous system in response to emotional stimuli.

The structure of this thesis is outlined as follows. Chapter 2 first presents the background work needed to thoroughly understand this research and a few previous research projects in this area, it then also explains our proposed framework of a predictive system. Chapter 3 begins by first describing the experimental protocol carried out for this research and then explains the analysis performed on the collected data. Chapter 4 depicts all of the results from our experiment and the performance of machine learning algorithms. Chapter 5 summarizes these results and concludes this thesis.

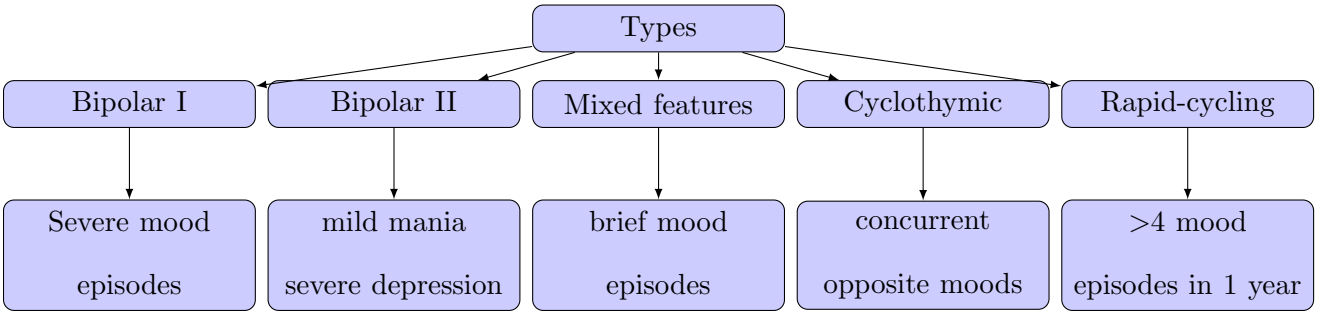
Abbreviation	**Definition**
HRV	Heart Rate Variability
IBI	Inter Beat Interval
Std/SD	Standard deviation
SampEn	Sample Entropy
DFA	Detrended Fluctuation Analysis
rr/RR/NN	inter -beat
ms	Milliseconds

2 Background

2.1 Bipolar Disorder

Patients suffering from Bipolar disorder experience repeated relapses of depressive and manic states. Pharmacotherapy and Psychotherapy is the only treatment of bipolar disorder available. These treatments are preventive measure of the illness, not curative. There is no known cure for bipolar yet, but preventive measure can minimize the damage, effects and intensity of a bipolar manic or depressive state.

Why is it necessary to identify and manage the emotional extremes exhibited by bipolar patients? In a manic state, a person is very impulsive and potentially take actions that can possibly have dire consequences and the likes of which they are unaware of at the time. On the other hand, a depressive state can force a patient possibly to the edge of suicide.



2.2 Bipolar States

Patients suffering from bipolar disorder experience major swings in their mood and emotional state. There are 4 known bipolar states.

- **Euthymic State**: Euthymic state on the other hand is the balanced state in which the patients experience the most stability in their mood [66]. Euthymic state is characterized by a normal, good quality and quantity of sleep, and well balanced social and work life.

- **Depressive State**: Hopelessness, anxiety, anger, Irritability, sadness, suicidal thoughts, minimized physical activity and social interaction are some of the common symptoms associated with depressive episode [54].

- **Manic State**: According to the DSM IV criteria [3], in a manic episode the patient has a "persistently elevated" mood. a state of very high self-esteem and grandiosity. They feel very energetic and feel rested after only a small amount of sleep. Their judgment is impaired, behavior gets reckless and acts tend to be impulsive.

- **Mixed State**: In a mixed state, depression and mania exists simultaneously, and symptoms of both are observed. Recognition of a mixed state is difficult, as sometimes it is an intermediary state of when a patient is moving from an extreme manic to a depressive state [30].

2.3 Social and Economic Burden

Bipolar disorder is one of the world's 10 most incapacitating disorders [15], and effects 5.7 million adults in United states alone. According to a systematic review, the prevalence of bipolar disorder in UK, Germany and Italy is approximately around 1% [17]. World mental health survey initiative in 2011 reported, an aggregation from 11 countries, a lifetime prevalence of 0.6% and 0.4% for Bipolar type 1 and type II respectively [42]. On top of this worrying prevalence across the globe, the disability caused by it is also significant. On average the onset of Bipolar disorder is at age 20 years [42] [20], because of which it causes more years of disability than any major illness including cancer [42]. This not only inflicts a considerable economic but social burden as well, with 93% of the caregivers of bipolar patients having reported to suffer from anxiety [5]. Patients with bipolar disorder tend to experience mild to severe restlessness and irritation. Caregivers are reported to have a great role in recognizing, intervening, and supervising in taking medication during these episodes [10].

2.3.1 Mortality Rate

Bipolar patients are at a high risk of suicide, 20 to 25% of individuals suffering with BD make suicidal attempts [42] [51]. They are also more likely to attempt suicide than any other depressed individual [54]. Alongside this, many studies have also indicated a simultaneous presence of another chronic disease in patients suffering from bipolar disorder [17], this increases the risk of mortality. Comorbid conditions were observed worldwide in BP patients [42]. according to a report in 2007 of UK the death rate of bipolar patients was 18%, with an attempted suicide rate between 21%-54% [16].

2.3.2 Economic Impact

Bipolar patients require continuous treatments, both inpatient and outpatient, inflicting an annual cost of more than $45 billion on the US economy in 1991 as estimated by one of the studies [27]. In 2009 another study [14] was conducted to include both the direct and indirect economic burden by bipolar disorder. Cost of treatment and utilization of health services is accounted as a direct cost, while lost work time cost etc. is categorized as an indirect cost. The study realized the direct cost as over $30 billion and the indirect cost as over $120 billion, estimating the total minimum cost as approximately $150 billion [14]. These large numbers have raised a serious concern, prompting the prioritization of researches on an alternate effective healthcare solution.

2.3.3 Impact on Caregivers

Caregivers are the people who help the patients manage the illness by recognizing, intervening, and supervising in taking medication during their episodes. They are in most cases partner, spouse or parent of the patient. In a survey conducted amongst caregivers of bipolar disorder in 2016 [10] it was reported that 49% of the caregivers had to make changes in their employment status because of the patients. The level of distress was noted to be the higher in women [26], with 72% of the total caregivers being females [10].

2.4 Current System in Place

Patients' diagnosis of the bipolar disorder is made using Diagnostic and statistical manual of mental disorders by American psychiatric association. On the other hand, the treatment of bipolar patients involves Pharmacotherapy and Psychotherapy. For the right medication and therapy, the current bipolar state of the patient has to be correctly identified. The current assessment system for bipolar patients includes a verbal interview with the psychiatrist, who then also asks the patients to fill out questionnaires and then comes up with a diagnosis of the current state accordingly.

The psychiatric interviews involve a verbal one-on-one between the patient and psychiatrist; during which psychiatrist asks questions and comes up with a diagnosis. During a psychiatric interview a psychiatrist might also use a rating scale, the score of which would help them with the diagnosis. There are numerous rating scales for depression and mania that can be used by psychiatrist, to evaluate the state of bipolar patient. One such scale is Hamilton Depression Rating Scale (HAMD), which was developed in 1957 and is highly preferred by psychiatrists [38]. 30-item Inventory of Depressive Symptomatology (IDS), and the 16-item Quick Inventory of Depressive Symptomatology Clinician rating (QIDS-C16) has also proven to have high psychometric usability [59], to be able to assess wide range of depressive symptoms [36] and has also found to be commonly used; especially in clinical trials and researches. Young Mania Rating Scale (YMRS) is a commonly used scale in clinical settings to measure the severity of mania [36]. There are also other scales like the Suicide Probability Scale (SPS), but their capability to identify any future suicide attempts by the patients is unclear [36].

Apart from the psychiatrists rating scales there are also self-reporting scales, one of which is QIDS-SR16, quick inventory of depressive symptomatology version for self-

reporting [59] [36]. There are also multiple mobile applications for self-management and logging, that give feedback based on the daily mood assessment that the patient would take through the App. Some of these systems are discussed in a later section (IV).

2.5 Physiological Biomarkers and sensors

Various sensors are available for measuring and recording the biometrics that vary state by state in a bipolar patient. Sensor used in preliminary research studies in the prediction and tracking of bipolar states is on rise.

2.5.1 Heart rate variability

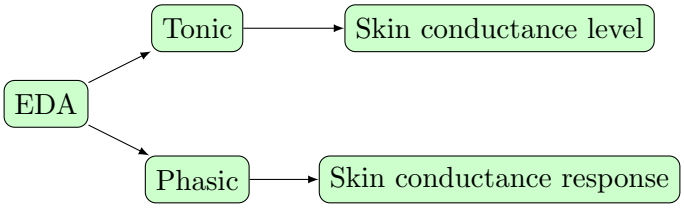
A heart rate variability(HRV) sensor measures the fluctuation of the persons heart rate from a normal average heart rate of 60 to 100 beats per minute. The sympathetic nervous system, that stimulate the body's fight-or-flight response, is responsible for the acceleration and deceleration of the heart rate.[66]

2.5.2 Electrodermal activity

Electrodermal Activity, commonly referred to as EDA, is the electrical phenomena in skin. EDA measures the effect on sweat glands and skin tissues when a small electric current is applied to it. Because sweat glands and the skin blood vessel are directly connected to the sympathetic nervous system, the EDA readings can be used to trace the emotional and cognitive state change and fluctuation. [22]

An EDA sensor applies a small AC or DC current to part of the skin, and measure the electrical resistance and capacitance of the skin tissues.

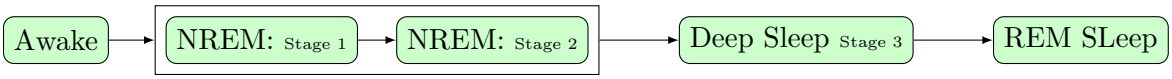
This technique is extensively used to study about the stress, anxiety and depression level in humans. Because Bipolar patients experience instability in their emotional state, clinical trials have shown that Electrodermal activity can be used to identify their depressive, manic or mix-state. [22]



EDA can be divided into two components, tonic and phasic. tonic is the skin conductance level and is the slow component, where as phasic is the rapid component indicating Skin Conductance Responses, that result from sympathetic neuronal activity.

2.5.3 Sleep Pattern

An advance sleep tracker sensor would record the duration of sleep and categorizes it into REM(rapid eye movement), NREM(non-REM), light and deep sleep. the time duration of each category of sleep plus the body movements recorded during the sleep gives us the quality of sleep.



- **NREM(stage 1)**: Here the person is lightly asleep. This stage lasts for about ten minutes during which the persons breathing and blood pressure is slowly decreases. People who have very irregular sleeping patterns might experience hypnic jerks during this stage quite often.[19]

- **NREM(stage 2)**: The actual sleep starts in this stage, where the heart rate and all other body activities are slowed down. both NREM stage 1 and stage 2 are commonly referred to as light sleep cycle.[19]

- **Deep sleep (stage 3)**: This stage of the sleep cycle kicks in about forty minutes after falling asleep.[19]

- **The Rapid eye movement sleep (REM)**: This is the last stage of a sleep cycle. While in this stage there is rapid movement of eye, increased heart rate and dreams.[19]

The REM and NREM category of sleep are each associated with specific physiological, neurological and psychological features which can be very helpful in predicting depression or mania. [19]

2.6 Related work

2.7 Behavioral Intervention Technologies

There are many behavioral intervention technologies for educational and intervention purposes for mental health. These behavioral intervention technologies include providing internet-based psychotherapies, web based and mobile based intervention and psychoeducation [48]. Studies have shown a clear long-term advantage of psychoeducation in terms of cost and better management of the disorder [60]. Psychoeducation for bipolar disorder includes giving patients in depth knowledge of the disorder, teaching them how to recognize the symptoms of each bipolar state and manage them accordingly. Internet has been identified as an essential source of information for caregivers and patients suffering from mental illnesses [44], hence the

feasibility of such a system can be established for the use in mental health care.

Web based intervention and psychoeducation technologies have a capacity to effectively aid bipolar and other mental disorders and improve their quality of life [48] [50] [28] [11]. MoodHwb [28] and Beating Bipolar [64] are some of the example technology. 'Beating bipolar' [64] is one of the web-based interventions for bipolar disorder. It contains educational and intervention content through an online program. Providing psychoeducation has encouraging results for long term management of bipolar disorder [64]. Although these web-based approaches have given promising results, additional research is still needed to establish the aggregate impact of this technology [64].

The prevalence of the mobile phones and their constant connectivity with people nowadays has shifted the focus largely towards mobile technologies [48]. Live communication with therapist, reminders, logging self-reporting data are some of the other features on which work has been done previously [48]. eMoods Bipolar Mood Tracker app [24], Intellicare [49], [13], MMD [40], and MONARCA system [6] are some of the similar mobile based applications for aiding mental illnesses especially mood disorder. Many studies have suggested that intervention with mobile based technologies can improve medication adherence in patients with serious mood disorder [58].

Personalized Real-Time Intervention for Stabilizing Mood (PRISM) [13], is one example of a mobile intervention system for bipolar disorder. Patients record their mood by responding to a set of questions, depending on the symptoms that are indicated by the patient, the app returns a self-management plan. Although interview with a clinician is independent, it helps in self-management of the diseases via psychoeducational intervention. There is clear evidence of the feasibility of using mobile devices, although more research is yet to be done on how effective they are [13].

Another example of such a mobile intervention is Mobile Mood Diary (MMD) [40].

It is inspired by the concept of a paper diary for bipolar patients for record keeping. With a less complex design to ensure adherence the MMD System was developed as a javaME application, that was easily downloadable on mobile phones. On a daily basis the patients would enter mood, energy and sleep record through a series of step by step entry fields, which would then be uploaded on the server. Summary with visualization would also be available for the patients to view. Both perspectives of end user and therapists were used to evaluate the usability of the system. A usability study and user trial were carried out to identify issues with the interface and working of the system for improvement. A 2-yearlong clinical evaluation was done using 9 bipolar patients in Ireland, and the results of the total usage and adherence (65%) of the system by the patients over these 2 years was quite high, providing us evidence that such a mobile system can be very engaging and suitable. Additionally, patients who are introvert and reticent about sharing their feelings, felts very comfortable reporting to a device. The 4 main benefits and reasons of using such a system are preference by youth, ease of use, privacy and timeliness [40].

A more advanced and a step ahead of just self- reporting applications is The MONARCA system [6]. Apart from using mobile phone application to record only self-reported mood data, MONARCA system also introduced activity monitoring through sensors in their system to set out early monitoring signs, along with visualization and coaching. The self-assessment consists of sections for each, Mood measurement, sleep quantity, Activity level and medicine adherence. Activity monitoring is done using phone sensors, such as accelerometer for physical activity and number of phone calls for social activity. Patients can get feedback from the applications though its graph visualization. The trigger feature of the application works using association rule mining. A 14-week feasibility trial was done to analyze the usability, suitability, usefulness and future compatibility of the system. The results of the trial showed

that the average adherence to the system by the patients was over 80%. This result plus the usefulness survey conducted in this study holds promises for using such systems to assist and manage bipolar disorder [6]. Several researches have substantiated the possibility and applicability of systems to use certain biomarkers to identify the bipolar state, in order to fill the gap caused by subjective data and delayed diagnosis. Some of the literatures on social interaction and physical motion, Heart rate variability, Electrodermal activity and sleep pattern for objective identification of bipolar states are discussed in the four subsections below.

2.8 Sensor based Technologies

2.8.1 Social interaction and physical motion

Symptoms of Bipolar disorder are mainly indicated through the change in a patient's behavior [53]. The key points that a physiatrist uses to assess a patient's state is their behavior which includes their physical activity and their social interaction; but all that is based on the patient self-reporting, which is highly subjective. This is where the use of mobile devices and sensors can be very advantageous [53].

In one such study [24], the researchers devised a smartphone-based system to recognize the state and the subsequent change of states in a bipolar patient. Visiting a doctor late not only has financial consequences but also has a deleterious impact on the health of the patient. Keeping that in mind, this study introduces a system that collects social interaction, physical motion and travel pattern data of the patients from sensors to drive a forecast system to predict the state of the patient. The study involved patients of age 18 to 65+ who were diagnosed with ICD10 classification. They applied linear discriminant analysis to identify the three states (classes) namely,

depressive, normal and manic. Moreover, after collecting the phone call data, sound, acceleration data and location data, the datasets were split into training and test data. Using Weka, they performed Bayes Classification model separately on data from each sensor. The forecasting process involves calculating the distances from the initial state to the newly predicted state by each classifier, weighting each distance based on the number of available training points and finally calculating the centroid. The centroid delineates the forecasted state of the patient. With the fusion of all the modalities; phone, sound, acceleration and location, the study resulted in an average accuracy of 76 percent in state recognition [24]. The results though not being very high, still highlight a fine pattern between the attributes and the state change.

acoustic voice analysis has also been something that has been greatly researched on for detecting mental disorder [21]. Some studies are also focused on analyzing voice to measure depression and mania in bipolar patients [18] [21]. In a 12 Week MONARCA study, text message, phone call and mobility data were collected from the smartphones of 28 participants. Voice features were obtained from the phone call data and Hamilton Depression Rating Scale (HAMD) and Young Mania Rating Scale (YMRS) were used to assess the patients state. The average accuracy of classifying bipolar state using the voice feature was between 61%-74%, further indicating promising results for real-time objective data collection to aid bipolar patients [18].

2.8.2 Electrodermal Activity

Electrodermal Activity (EDA) readings can be used to trace the emotional and cognitive state change and fluctuation. EDA has been shown to change along with the pathological mood states [23], hence proven to be a biomarker that can be used to track and predict Bipolar states.

In a Book published in 2016, "Advances in Electrodermal Activity Processing with Applications for Mental Health" [23], chapter 5 outlines experiments carried out on bipolar patients to specify how EDA changes with each mood state, in order to prove EDA as a reliable biomarker to recognize bipolar state. 10 bipolar patients were recruited for an emotional elicitation protocol which involved a slideshow of negative emotionally evocative pictures from IAPS and some pictures from TAT [23]. International Affective Picture System (IAPS) is a database of pictures, developed by the Center for the Study of Emotion and Attention (CSEA) at the University of Florida, to evoke different emotions [37]. Thematic Apperception Test (TAT) are a set of ambiguous pictures, the participants are asked to tell a story about each picture and their response indicates certain Psychometric characteristics, because it evokes the subconscious of the participant [37].

Before each round of the experiment, a psychiatrist would interview the patient and assign them with a mood label. During the experiment the patients EDA signals were collected using BIOPAC MP150. After decomposition of EDA signal into phasic and tonic components different features such as mean, maximum and standard deviation of phasic and tonic were extracted for analysis. EDA data collected from each round would have a mood label associated with it for supervised learning. a k-Nearest Neighbor (k-NN) classification model was developed based on the data to identify different states. The results of the classification had an accuracy of over 80%.

Further statistical analysis on the data gave evidence of how sympathetic activity decreases in a depressed patient represented by low EDA, and how phasic attributes are affected by mood change. A group of healthy participants were also examined as a control, confirming that analysis of Electrodermal activity is feasible for identifying pathological mood in bipolar patients or other mental illnesses [23].

The Electrodermal activity signals that are received from the sensor have to go through a deconvolution process before features can be extracted for classification and prediction. Another preliminary study [22] as part of the PSYCHE project, shows the correlation between Electrodermal activity and bipolar states, and also discusses the deconvolution analysis process.

Electrodermal activity signal has two components, tonic and phasic. Tonic is the skin conductance level and is the slow component, while phasic is the skin conductance response and is the fast component [22]. Due to short intervals of the phasic component there is overlapping of consecutive physic, so in order to ensure proper decomposition of EDA signal into their respective components a deconvolution process has been proposed [9]. Since the introduction of this process by Benedek, has been applied by many researches that involved EDA analysis. In this technique Skin conductance (SC) is established as the convolved signal of sudomotor nerve activity (SMNA) and the impulse response (refer to equation 2.1 below).

$$SC = SMNA * IRF \tag{2.1}$$

The biexponential Impulse Response Function (IRF) is shown in equation 2.2 below:

$$IRF(t) = (e^{\frac{-t}{t1}} - e^{\frac{-t}{t2}}).u(t) \tag{2.2}$$

Sudomotor nerve activity (SMNA) is basically driver tonic plus driver physic. Therefore, deconvolution of the EDA signal with the biexponential Impulse Response Function (IRF) is done to get sudo motor nerve activity (SMNA) signal, and decomposition of which would give us tonic and phasic as a separate entity (Refer to Figure 1).

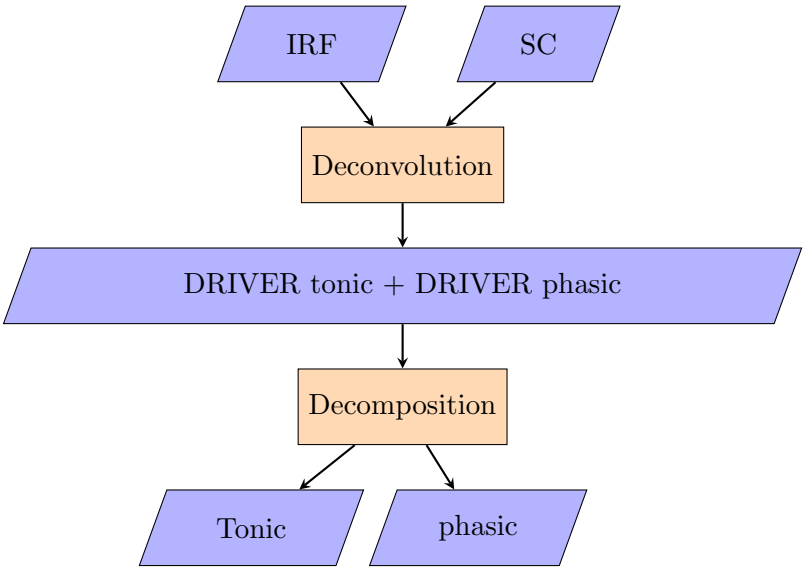


Figure 2.1: Decomposition of Electrodermal Activity signal

It has been established that EDA collected at Palms and feet is more reliable than any other part [55] [33]. Taking this fact into account, the MONARCA project also introduced a smart sock, that depicts an actual sock both in appearance and in comfort, and has electrodes embedded in it to measure Electrodermal activity. The project used the smart sock in a feasibility study involving healthy participants [33], Further research on this textile involving Bipolar patients is underway.

Heart Rate Variability

Another physiological biomarker for identifying mood state and predicting mood change is heart rate variability. The mood changes in patients suffering from bipolar disorder are associated with dysregulation of the autonomic nervous system, and analysis of the heart rate variability can give us an understanding of it [39] [2]. Heart rate variability is a measure of the regularity of the heart rate and has been manifested to be a promising and suitable indicator to gauge the response of the autonomic nervous system.

A 14-week long research study [67] was carried out in the University hospital of Strasbourg and Geneva on 14 bipolar patients. Through the PSYCHE platform, using a sensorized t-shirt with ECG electrodes embedded in it, the researchers collected HRV data from the patients. Each patient was given different psychotropic medications, which included mood stabilizers, antipsychotics, benzodiazepine-like and antidepressants. Psychiatrist interviews were done, and each patient's mood state was identified before each acquisition.

After the preprocessing of the ECG data, time domain, frequency domain, and non-linear features were extracted. Non-linear HRV features that were evaluated included sample entropy, approximate entropy, Poincare, and Detrended Fluctuation Analysis (DFA). After feature extraction a N M matrix of the features against the number of acquisitions were obtained. In order to reduce the dimensionality of the data, principal component analysis was applied. Because mood change in bipolar patients is dependent on the current mood (markov chain) [68], the current mood of the patient was also included as one of the features. The learning algorithm used was support vector machine (SVM), and it was trained and tested on the data of each participant individually, achieving an average prediction accuracy of 69%. It

was also observed that non-linear features, Poincare SD1 and SD2 showed a more notable change with mood. Although the prediction accuracy of the system is not very high, it affirms the use of Heart rate variability as a biomarker for mood changes in patients suffering from bipolar disorder or other mood disorders.

Most of the researches are focused to a greater extent on identifying bipolar depression, however one study [25] specifically analyses the HRV time, frequency and non-linear features in manic bipolar patients. 23 manic bipolar patients were examined, and their manic symptoms were evaluated using Young Mania Rating Scale (YMRS). The results of the study concluded an inverse relationship between HRV and the score from YMRS, meaning the more severe the mania the lower the HRV. Nonlinear HRV features include complexity measure of the heart rate such as entropy and Correlation Dimension, which was also shown to decrease in manic patients in the study [25].

Sleep Pattern

Along with heart rate variability, it has also been made evident that analysis of sleep cycle can help identify depressive state in bipolar patients [46]. In one of the European research studies [46], a sensor-based T-shirt was used to measure Electrocardiography signals (ECG) and body motion from 15 bipolar patients during night time. The study only focuses on predicting depressive state of the bipolar patient. Before every data acquisition the psychiatrist would assess the actual current state of the patient.

Using the collected data, the heart rate variability (HRV) and sleep stages were estimated for analyzing and predicting depressive episodes in Bipolar patients. The standard Time, frequency and non-linear features of HRV are all considered for analysis. As for sleep, the researchers used an already trained supervised Artificial Neural

Network model for predicting the sleep stage (Wake, NREM, REM) when HRV and body activity data was provided to it. The following sleep related features were extracted for analysis in this study:

- Time spent in bed
- Sleep latency
- Total time spent in bed but not asleep
- Total sleeping time
- Sleep efficiency as sleeping time/ total time in bed.

it was observed that total sleep time and sleep efficiency differ appreciably in depressive and non-depressive state of the patients. In summary the results of the study also showed that a depressed state in a bipolar patient is characterized by a decreased HRV, and increased sleep time and sleep efficiency [46]. The paper also asserts the possibility of using a home-based monitoring system for patients suffering from psychiatric disorders [46].

Disturbed sleep is a very common symptom of depression as proven by many studies [52], hence they are a viable biomarker. While many studies have reported insomnia (loss of sleep) as being a symptom of mania [12], and hypersomnia as a symptom of a depressive state [52], one study has also highlighted that hypersomnia is an indication of relapse to mania in bipolar patients [32]. Therefore, sleep features can be another predictor for bipolar state. While the work on predictive systems using sleep cycle analysis has shown some hopeful results, research in this area still has a long way to go.

2.9 Our Proposed Approch

predictive models discussed in section 2.8, are based on sensor to collect bio-marker data, accuracy of which is significant and favorable for predicting early warning signs. On the other hand, the feasibility and usability study of the mobile applications discussed in 2.7, holds promises for using mobile technologies to assist and manage bipolar disorder. Our approach is aimed towards a hybrid of Sensor based predictive model and mobile application , which would be based on objective data instead of self assessment. [41]

The proposed framework would consist of four major components:

- Sensors: Sleep tracker, HRV and EDA sensor
- Self-reporting (Mood chart)
- Trained classification models and a prediction fusion algorithm
- Mobile application as front end for visualization and computation.

Mood chart and data acquisition: The mood chart offers patients the ability to log their mood several times during the day using the mood scale available on the mobile application.

Sensors and data acquisition: Day to day sleep, HRV and EDA data is acquired using the wearable sensors. The collected data will undergo feature extraction. The features extracted from each sensor data serves as attributes to the classifiers. Using the fusion algorithm, the output of the classifiers along with the self- reported mood will give a prognosis of the current bipolar state.

Mobile platform: The mobile application offers users a visualization tool in the form of a dashboard. Secured access for the patient or any other authorized

personnel such as family or therapist will offer opportunity to view the day to day summarization or various sets of data acquired through self- reporting and sensors. However, giving authorization to access user data causes an ethical issue that is yet to be worked out by researchers in developing an assistive system.

2.9.1 Data Sources and Predictive models

- Electrodermal Activity sensor
- Heart rate variability sensor
- Sleep Tracker
- Self reporting

Data collected from all three sensor-based sources are subject to preprocessing and feature extraction. The features extracted of each sensor modalities serve as attributes to estimate the state. Principal component analysis can be used to reduce the dimensionality of our data and select the relevant features. In the process of building the prediction models, classification techniques are applied to training data sets of sleep, HRV, and EDA individually yielding the relationship between their features and the bipolar state only to get a learned classifier of each sensory modality.

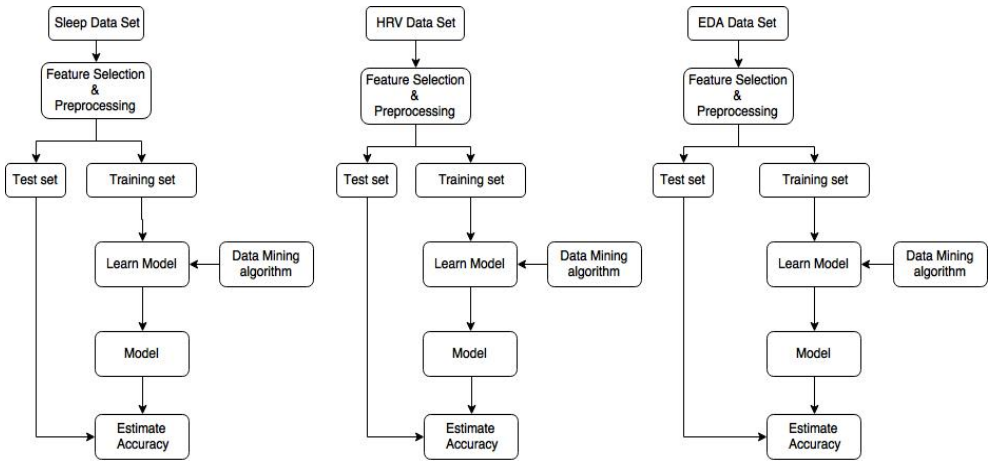


Figure 2.2: Training and Testing Routine

2.9.2 Feature Extraction

Following features from the sleep, HRV and EDA data would be extracted for analysis and prediction model.

Sleep Features	
TPS	Time spent in bed prior to sleep
TT	Total time spent in bed
TST	Total sleep time
TSI	Number of times sleep was interrupted
DREM	Duration of REM sleep period
LREM	The mean REM latency

HRV Fearures	
Poincare SD1	Standard deviation perpendicular (i.e. width) to the identity line of Poincare plot
Poincare SD2	Standard deviation parallel (i.e. Length) to the identity line of Poincare plot
SampEn	Sample Entropy, Measure irregularity of the IBI series
DFA1	Detrended Fluctuation Analysis: Short term
DFA2	Detrended Fluctuation Analysis: Long term
MeanIBI	Mean of the inter beat interval
SDNN	Standard deviation of the NN interval/ IBI
MeanHR	Mean of Heart Rate
SDHR	Standard deviation of heart rate

EDA Fearures	
MAX-Tonic	Maximum value of the tonic driver curve
MAX-Phasic	Maximum value of the phasic tonic curve
AUC-Tonic	Area under the tonic driver curve over time
AUC-Phasic	Area under the phasic driver curve over time
Mean-Tonic	Mean value of the tonic driver component
Mean-Phasic	Mean value of the phasic driver component
STD-Tonic	Standard deviation of the tonic driver component
STD-Phasic	Standard deviation of the phasic driver component

2.9.3 Fusion of all models

Once we have the predictions from all the three classifiers, an effective fusion algorithm would be employed to combine the outputs. The weighted averaging method is one of the many methods that can efficiently combine the outputs of the classifiers [63]. The subjective, self-reported mood data that is acquired from the patient logs will be assigned lesser weight. On the other hand, the weight of the three-classifier output will be assigned the respective relative classifier accuracy as their weight [63]. Hence the higher the accuracy of the classifier the more weight its output has in the final fusion.

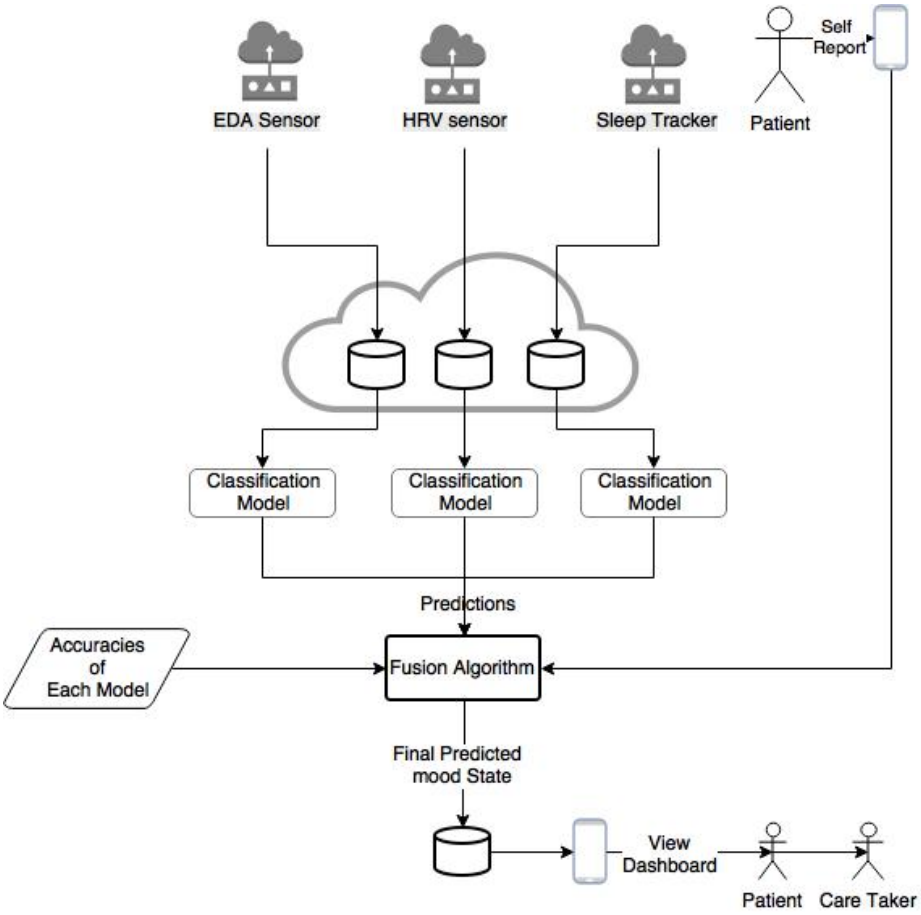


Figure 2.3: System Process flow Diagram

2.9.4 Data collection

We conducted a preliminary data collection study for analysis and design of the model. We collected data from Electrodermal activity sensor and Hear rate variability sensor from 50 healthy participants during normal and negative valence scenarios. The data collected was subjected to feature extraction and a labeled data set was created for training a predictive model for psychological changes from the collected physiological features. Though we researched upon and included sleep features in our proposed framework, the scope of this exploratory study includes HRV and EDA features only. The study covers:

- The computation of the HRV and EDA features
- Analyze variations in features
- Ability of EDA to identify the activity of the autonomic nervous system in response to emotional stimuli
- Ability of HRV to identify the activity of the autonomic nervous system in response to emotional stimuli
- Machine learning algorithms recognition of emotional regulation occurring through elicitation.

3 Implementation

3.1 Sensor

The sensor used in this thesis is E4 sensor by Empatica. It is a wearable wristband that collects physiological data. It allows real time streaming and has a flash memory to store data of up to 60 hours. It contains a PPG sensor for HRV, EDA sensor and Internal Real-time clock. We collected both sensor modality using a single wrist band.

3.2 Data Collection

This user study dealt with only with healthy participants and has limited scope. We Investigated how psychological changes, affect physiological responses. The project involved:

- Design of an emotional stimuli study to investigate physiological responses (HRV and EDA) with respect to psychological changes.
- Studying the correlation between heart rate variability and emotional stimuli.
- Studying the correlation between Electrodermal activity and emotional stimuli.
- Building predictive models for negative valence emotion from the data set gathered.

3.3 IRB protocol

3.3.1 Primary Endpoint/Event/Outcome

The outcome of this study was set of Heart rate and EDA data in response to an emotional elicitation in healthy adults. The primary objective was to achieve a relationship between the two.

3.3.2 Interventions

The study includes display of a slide show with a set of pictures from the International Affective Picture System (IAPS) (developed by the Center for the Study of Emotion and Attention (CSEA) at the University of Florida). The pictures are emotionally evocative to evaluate the change in heart rate and EDA.

3.3.3 Interactions

During the slide show the participants would be filling out a questionnaire, which contains valence rating for each picture.

3.3.4 Study Design

Each research participant spends about 20 minutes in the laboratory. This time frame consists of 8 minutes resting period prior to the experiment, 5 minutes of slide show consisting of a series of pictures, 2 minutes of audio playing and 5 minutes of resting period for post-experiment survey and briefing. Experiment Steps:

- Participants would be asked to wear the wristband (which would be a sensor to record Heart rate and EDA)

- Participants will watch a slideshow of pictures followed by a set of audios (Details mentioned in the section below)

- After each image/audio participants will be asked to answer a question on the questionnaire. This question would be repeated for each image/audio after each slide, and consists of a rating scale based on Self-Assessment Manikin (SAM: Bradley & Lang, 1994):

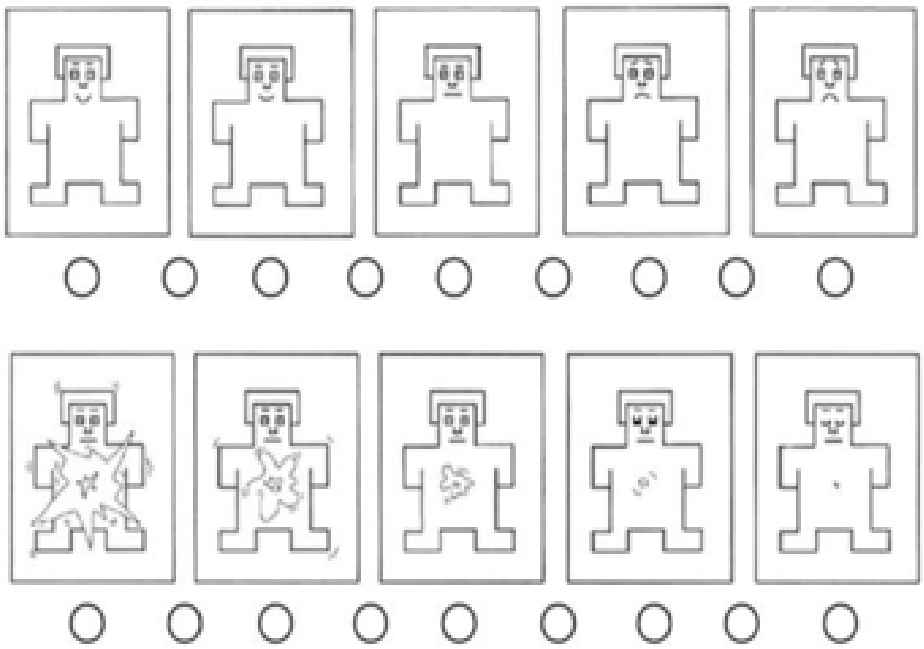


Figure 3.1: SAM

3.3.5 Study Procedures

- Obtain informed consent from each individual prior to any activity.
- Provide them with a Questionnaire to be filled during the experiment. The form would be anonymous, and the form-ID would serve as an identifier.
- Before each participant experiment, the wrist band would be cleaned and dried completely for any trapped moisture, bacteria or dirt, that may cause any irritation. The disinfection process would include cleaning all parts of the device, that comes in contact with the skin, with cotton soaked with a small quantity of ethyl or isopropyl alcohol. Before switching between users, we will make sure all residual cleaning solution has dried. (https://support.empatica.com/hc/en-us/articles/204501555-Device-care-and-maintenance)

3.3.6 Equipment's Used

E4 wristband sensor and a mobile device was used in the study for data collection.

E4 wristband (https://www.empatica.com/research/e4/) is a wearable research device for physiological data acquisition. The Band is made up of Polyurethane material. The data from the sensor was streamed via a IOS application in to a MySQL database.

Figure 3.2 above shows a simple UI for IOS application built to stream data from the sensor. The 'scan and connect' button connects to the E4 sensor via bluetooth. the top text box is to enter the participants ID, then on clicking 'Go' it takes you to the next page to record the timestamps for that participants study. All the participants data is inserted into a MySQL database with participant ID as identifier.

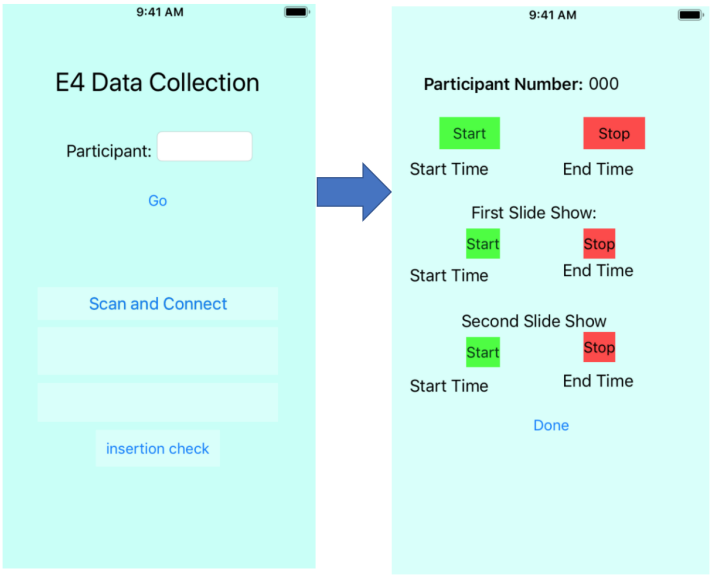


Figure 3.2: Mobile app to connect to the sensor and collect data for the study

3.3.7 Questionnaire

The Questionnaire filled by the participants during the experiment consisted of valence and excitement scale for each image. The participants would rate each image. The scale in the Questionnaire is based on Self-Assessment Manikin (SAM: Bradley & Lang, 1994). SAM is a validated non-verbal pictorial assessment technique that measures the personal response of the participant to each picture and audio.

3.3.8 Elicitation protocol:

The following emotional elicitation protocol that we used, to investigate the relation between emotion and physiological changes, is based on:

- The International Affective Picture System (IAPS), developed by the Center for the Study of Emotion and Attention (CSEA) at the University of Florida.
- The International Affective Digital Sound (IADS), developed by the Center for the Study of Emotion and Attention (CSEA) at the University of Florida

A set of pictures from IAPS and digital sounds from IADS would be used as emotional stimuli for our experiment. IAPS is a set of photographs that provides standard emotional stimuli for PAD emotional states (Pleasure Arousal and Dominance). Similarly, IADS is a set of emotionally evocative sound stimuli, which we will be using alongside (http://csea.phhp.ufl.edu/Media.html). We selected images and audios from IAPS and IADS with high negative valence as our emotional stimuli.

Participants were seated and briefed about the study and the procedure. They were then asked to fill out the consent form.	
Upon briefing and signing of the consent form the participants were then asked to wear a sensor around their wrist, which would record their physiological data.	
Facing the screen in a dimmed light room, they would then rest and sit idle for few minutes. Any baseline measurements were recorded during this phase.	3 Minutes
Then a series of IAPS pictures with high negative valence are displayed.	4 minutes
Following that, a set of digital sounds (IADS) with negative valence is played	2 minutes
Rest period	
This marks the end of the data collection. Participants are free to ask questions if they have any regarding the purpose of the study and are also provided with a list of campus counseling/mental health resources that are available.	

Table 3.1: Experimental Protocol

3.3.9 Environment

The experimental environment consisted of a display projector screen with a table and chair set in front of it. The participants were seated directly facing the display screen from a respectable distance in a dimmed light room. Figure 3.2. shows a picture of the setup taken during the study.

Figure 3.3: Experimental Setup

3.3.10 Risks

There was minimal to no risk of injury or physical harm to the participants. Some images had high negative valence, hence participants with any possible cardiac risk or history were not selected for the experiment. The participants were seated at a respectable distance from the display screen to avoid any stress on eyes. The digital sounds were played with controlled volume to negate any risk of hearing damage.

3.3.11 Ethical issues addressed

The research protocol addressed the following ethical issues:

- **Informed consent:** The informed consent from the participant is obtained right before the study begins. The consent contains the details of the research setup, purpose, duration, participants rights regarding autonomy and withdrawal at any point, information about the data collected, contact information for concerns and a clear statement that there is no cost associated with the participation. The inclusion criteria for the study required the participants to be adults who can provide informed consent.

- **Data confidentiality:** To insure data integrity and security, all the data is anonymous and is stored and backed up on a password protected university owned laptop, in accordance with the institutes data storage standards. The copy of the consent for or any other research study information were not placed in the participants employment and or educational records.

- **Privacy protection:** The study was conducted in a closed room, with no audience to protect participants privacy interest. The procedure was explained to the participants by the investigator, and any questions they may have were also answered in a closed room.

- **Recruitment of participants:** To recruit participants an advertisement email was sent to all the students and faculty in the department, and anyone who fulfilled the inclusion criteria were able to participate voluntarily. Participants self-identified themselves in response to the email that was sent out. No participants were recruited based on any information contained in any private or protected records.

3.4 Data Analysis

The data collected from each participant was their EDA and HRV data. There were two sets of data for each sensor modality, the baseline data and negative valence data. All the data from each phase of the study (baseline and negative valence), was subjected to feature extraction for further analysis. Figure 3.4 shows the flow of the data analysis process.

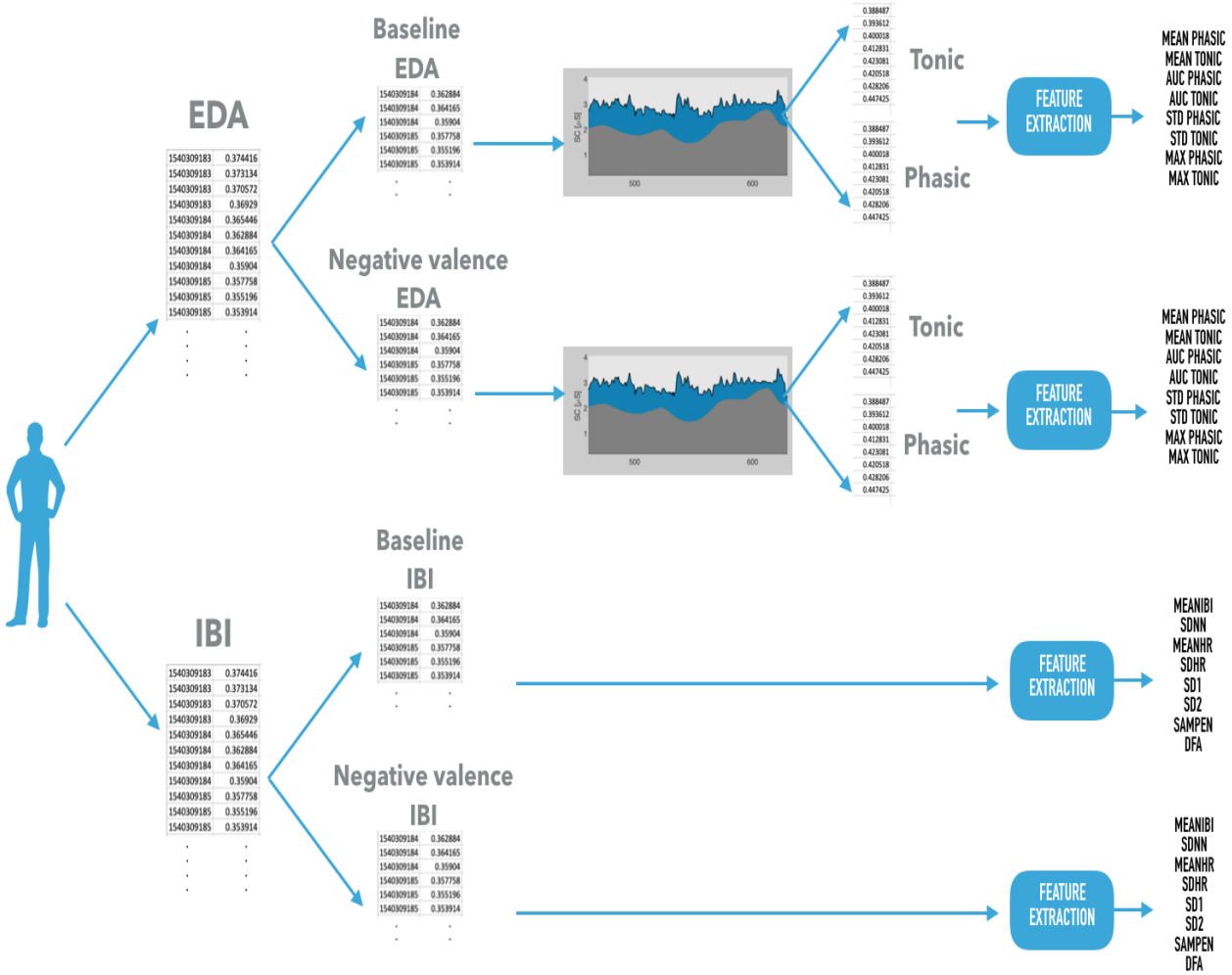


Figure 3.4: Data analysis

3.4.1 HRV Analysis

The tool used for the analysis of HRV is the Heart Rate Variability analysis software (HRVAS) by John T. Ramshur [56]. Time-domain and Nonlinear features were calculated for analysis.

- Time domain Analysis: MeanIBI, SDNN, MeanHR, SDHR
- Nonlinear Analysis: SD1, SD2, SampEn, DFA

Poincare

Poincare plot is the plot of IBI_n against IBI_{n-1} [56]. It represents the correlation between successive IBI (interbeat interval). SD1 is the Standard deviation perpendicular (i.e. width) to the identity line of Poincare plot. It represents the short-term variability of the IBI. calculated as shown in equation 3.1 below:

$$SD_1 = \frac{1}{2} std(rr_n - rr_{n-1})^2 \tag{3.1}$$

SD2 is the Standard deviation parallel (i.e. Length) to the identity line of Poincare plot. It represents the long-term variability of the IBI. SD2 is calculated using the standard deviation of the IBI, and the standard deviation of the successive differences of the IBI as shown in equation 3.2 below:

$$SD_2 = 2 * std(rr)^2 - \frac{1}{2} std(rr_n - rr_{n-1})^2 \tag{3.2}$$

SampEn

Sample entropy measures the complexity. Higher the SampEn, higher the complexity of the IBI data. Lower the SampEn lesser the complexity and more self-similar

the data [56] [57]. Literature [56] describes the calculations for sample entropy.

DFA

Detrended fluctuation Analysis (DFA), measure the self-similarity of the IBI signal [56][61][65] the calculations are performed on subsets of the data. DFA requires large dataset [61], so we were unable to calculate DFA of some of the participants whose IBI data acquired from the sensor was insufficient.

The IBI series (RR interval) is integrated using the following equation:

$$y(k) = \sum_{j=1}^{k} (RR_j - RR) \tag{3.3}$$

The integrated series calculated from this is then split into segments. A least square line is fitted within each segment $y_n(n)$. Then the integrated series is detrended and the root mean fluctuation of this series is calculated by:

$$F(n) = \sqrt{\frac{1}{N} \sum_{k=1}^{N} [y(k) - y_n(n)]^2} \tag{3.4}$$

$F(n)$ is the gap for a certain window size, N is the number of points, $y(k)$ value of time series at time k, $y_n(k)$ is the value of the regression point at time k. [65] $DFA(1)$ is the short-term Detrended Fluctuation Analysis, and $DFA(2)$ is the long-term Detrended Fluctuation Analysis. In our case the break point for $DFA(1)$ and $DFA(2)$ is at 13 beats. Meaning 13 marks the end of $DFA(1)$ and start of $DFA(2)$.

MeanIBI

Mean of the inter beat interval series

$$mIBI = \frac{\sum_i^N (ibi_i)}{N} \tag{3.5}$$

SDNN

Standard deviation of the NN interval/IBI

$$SDNN = \sqrt{\frac{\sum_i^N (RR_i - mRR)^2}{N-1}} \tag{3.6}$$

MeanHR

Heart rate can be calculated from IBI by:

$$HR = \frac{60000}{ibi} \tag{3.7}$$

Mean of Heart Rate was calculated as:

$$mHR = \frac{\sum_i^N (60000/RR_i)}{N} \tag{3.8}$$

SDHR

Standard deviation of heart rate.

$$SDHR = \sqrt{\frac{\sum_i^N ((60000/RR_i) - mHR)^2}{N-1}} \tag{3.9}$$

3.4.2 EDA Analysis

The skin conductance signal has two components, the skin conductance level also known as Tonic component, and the skin conductance response also known as the phasic component [34]. The phasic and tonic components are derived from SC in two steps, first we deconvolute the SC signal with the biexponential Impulse Response Function (IRF), the resultant is the Sudo Motor Nerve Activity (SMNA) which is then decomposed to get the driver tonic and driver phasic [8] [34]. The tool used for analysis of skin conductance in this experiment is 'Ledalab' developed by Dr. Mathias Benedek [7].

Following features were calculated from the tonic and phasic components of each participant for each part of the study:

- Mean Phasic: Mean value of the phasic driver component
- Mean Tonic: Mean value of the tonic driver component
- AUC Phasic: Area under the phasic driver curve over time
- AUC Tonic: Area under the tonic driver curve over time
- STD Phasic: Standard deviation of the phasic driver component
- STD Tonic: Standard deviation of the tonic driver component
- Max Phasic: Maximum value of the phasic tonic curve
- Max Tonic: Maximum value of the tonic driver curve

3.5 Machine learning models

We used three algorithms to build our machine learning models. Each one is briefly introduced in the sections below

3.5.1 Support Vector Machine

SVM is a supervised learning model. It finds an optimal separating hyperplane on our dataset with binary classes. It then performs non-linear classification using kernal method which involves finding patters. [31]. SVM has been shown to get very high accuracy [1]

3.5.2 Linear Discriminant Analysis

Linear Discriminant Analysis finds linear feature set which best discriminate the two classes which we are trying to predict [47]. For binary class, as in our case, the n-dimentional data is given a direction w and projected on a line [31]. inter and intra class scatter are used to create criteria for class separability. Literature , briefly explains Linear Discriminant Analysis applied to a 2-class problem [4].

3.5.3 Binary Decision tree

Binary decision tree has a tree data structure with boolean function. The leave nodes are either 0 or 1, binary class. The path from the root node all the way down to the leave node represents the assigned class.

4 Results

4.1 Features

In this study, results were obtained considering data gathered from 50 healthy participants between age 18 to 35. Each acquisition of each participant had two segments; the baseline HRV and EDA collected during the resting phase, and HRV and EDA data collected during the emotional stimuli phase (denoted as negative valence session).

For HRV analysis the nonlinear and time domain features, as described in previous section, were calculated from the data collected from each participant during both phases of the study. Table in figure 4.1 below shows complete HRV features of all the participants during baseline. Table in figure 4.2 below shows complete HRV features of all the participants during Negative valence phase.

Table in figure 4.3 below shows complete EDA features of all the participants during baseline. Table in figure 4.4 below shows complete EDA features of all the participants during Negative valence phase.

Gender	SD1	SD2	SampEn	DFA(all)	DFA(1)	DFA(2)	MeanIBI	SDNN	MeanHR	SDHR
Male	54.7	97.5	3.045	1.014	0.989	1.108	989.8	79.1	61	5.4
Female	75.9	87.1			0.577		869.9	81.7	69.6	6.9
Male	66	97	1.969	0.782	0.789	0.74	820	82.9	73.9	7.5
Female	47.7	92.4	2.708	0.939	0.948	0.969	783.9	73.5	77.2	7.2
Male	65	133.6			1.023		906	105	67.2	8.3
Male	44.7	50.3	1.985	0.758	0.501	0.805	637.3	47.6	94.7	7
Male	57.1	113.8	2.225	1.009	0.933	1.133	815.6	90	74.5	8.7
Female	48.5	61.8	2.912	0.495	0.767	0.439	820.5	55.6	73.5	5.2
Male	15.9	51.6	1.544	0.749	1.284	0.547	571	38.2	105.5	7
Male	32.7	42	1.749	0.633	0.959	0.513	703.8	37.5	85.5	4.6
Female	48.1	95.3	2.134	0.781	1.117	0.583	856.6	75.5	70.6	6.1
Male	42.2	68.9	1.782	0.804	1.028	0.813	887.4	57.1	67.9	4.4
Male	40.7	124.1	1.224	0.866	1.387	0.792	730.8	92.4	83.4	10.1
Female	46.2	80.5	2.001	0.741	1.083	0.718	792.4	65.6	76.2	6.4
Male	33.7	69.6	1.968	0.891	0.884	0.913	713.7	54.7	84.5	6.3
Male	82.9	132.4		1.033	0.865	1.14	781.9	110.5	78.4	12.3
Male	36.8	88.1	2.051	0.945	1.305	1.013	845.9	67.5	71.4	6.6
Female	22.7	71.7	1.935	1.127	1.256	1.176	815	53.2	73.9	5.1
Male	20.4	59.9	1.506	0.976	1.352	0.858	573.6	44.7	105.2	7.9
Male	38.7	42.8	1.484	1.034	0.535	1.114	714.6	40.8	84.2	4.6
Male	59.2	130.8	2.639	0.939	1.001	0.894	884.2	101.5	68.8	8.3
Male	57.6	89	0.105	0.452	1.079	0.225	803.7	75	75.3	6.9
Male	21.2	53.9	1.52	0.798	1.329	0.655	650.7	41	92.6	5.9
Female	40.7	86.8	2.223	0.74	1.153	0.617	742.8	67.8	81.5	7.5
Female	44.8	82.9	2.497	0.873	0.915	0.769	689.3	66.7	87.8	8.2
Female	41.4	83.1	2.268	0.965	0.903	0.992	673.7	65.6	89.9	8.3
Female	20.2	45.3	1.711	0.978	0.952	0.925	730.1	35.1	82.4	4
Female	29	61.7	2.082	0.967	0.985	0.984	743.9	48.2	81	5.5
Female	54.9	71.5	2.485	0.763	0.787	0.791	853.7	63.8	70.7	5.3
Female	83.4	128.2	1.946	0.752	0.545	0.956	862.6	108.2	70.7	9
Female	35.5	48.6	1.883	0.631	0.756	0.57	593	42.6	101.6	6.5

Figure 4.1: HRV during baseline

Gender	SD1	SD2	SampEn	DFA(all)	DFA(1)	DFA(2)	MeanIBI	SDNN	MeanHR	SDHR
Male	68.9	90.7	2.565	0.765	0.674	0.804	1029.1	80.6	58.7	4.9
Female	64.3	71.7	2.789	0.71	0.623	0.746	866.5	68.1	69.7	5.5
Male	61.6	72.7	2.818	0.745	0.816	0.715	828.4	67.4	72.9	6
Female	54.7	92.1		0.58	0.983	0.354	823.3	75.7	73.5	6.7
Male	42.4	73.9	2.028	0.632	0.928	0.562	922.1	60.2	65.4	4.6
Male	27.3	37.5	1.816	0.785	0.643	0.865	634	32.8	94.9	5
Male	53.2	85		0.474	0.975	0.286	771.4	70.9	78.4	7.3
Female	28	30.4	1.707	0.458	0.606	0.341	867	29.3	69.3	2.5
Male	27.2	53	1.842	0.771	1.014	0.767	682.3	42.1	88.3	5.4
Male	16.4	24.5	1.512	0.695	0.961	0.594	731.6	20.8	82.1	2.3
Female	32.1	68.8	1.831	0.682	1.16	0.552	863.9	53.7	69.7	4.2
Male	40.7	67.1	2.001	0.867	0.864	0.939	918.2	55.5	65.6	4.1
Male	42.7	90.1	2.512	0.744	1.013	0.725	843.8	70.5	71.6	6.4
Female	44.3	72.9	2.303	0.736	1.04	0.7	820.5	60.3	73.5	5.6
Male	43.2	64.7	2.377	0.894	0.552	1.046	777.5	55	77.6	5.5
Male	62.9	111.5	2.288	0.857	0.763	0.816	791.1	90.5	76.9	9.1
Male	46.2	70.6	1.878	0.59	0.969	0.471	848.2	59.6	71.1	5.1
Female	42.4	63.7	1.825	1.057	0.715	1.199	864.5	54.1	69.7	4.7
Male	29.2	48.9	1.702	0.725	1.09	0.649	566.5	40.2	106.4	7.2
Male	33.2	33.5	1.612	0.669	0.57	0.641	715.7	33.3	84	3.9
Male	37.9	101.2	2.3	0.847	1.094	0.798	803.7	76.4	75.3	7.2
Male	51.6	76.6	2.338	0.701	0.757	0.691	831.3	65.3	72.6	5.8
Male	17.7	39	1.59	0.936	0.943	0.955	699.8	30.3	85.9	3.7
Female	48.1	74.7	2.476	0.621	0.895	0.607	781.2	62.8	77.3	6.2
Female	41.4	83.1	2.268	0.965	0.903	0.992	673.7	65.6	89.9	8.3
Female	31.9	93.8	1.373	0.576	1.276	0.256	1140.7	70.1	52.9	4.3
Female	20.4	38.5	1.635	0.878	1.015	0.845	705.5	30.8	85.2	3.7
Female	27.9	57	2.054	0.856	0.912	0.925	765.8	44.9	78.6	4.7
Female	56	72.3	2.442	0.706	0.753	0.655	867.3	64.6	69.6	5.2
Female	77.2	122.2	2.413	0.599	0.617	0.662	817.5	102.2	74.2	9.2
Female	26.5	42.4	1.696	0.706	0.778	0.639	611.8	35.3	98.4	5.6

Figure 4.2: HRV during negative

Gender	mean phasic	mean tonic	mean eda	sd phasic	sd tonic	sd eda	max phasic	max tonic	max eda	auc phasic	auc tonic	auc eda
Male	0.046	1.209	1.216	0.063	0.179	0.172	0.358	1.584	1.584	6.276	1072.022	1078.585
Male	0.148	2.259	2.291	0.230	0.413	0.409	0.809	3.221	3.221	8.348	593.769	602.229
Female	0.002	0.230	0.231	0.002	0.016	0.016	0.015	0.274	0.274	0.152	146.233	146.388
Male	0.005	0.395	0.396	0.006	0.040	0.040	0.031	0.474	0.474	0.471	295.103	295.580
Female	0.004	0.071	0.072	0.004	0.007	0.007	0.021	0.110	0.110	0.465	85.982	86.449
Male	0.010	0.236	0.238	0.013	0.039	0.038	0.096	0.337	0.337	1.389	198.345	199.744
Male	0.003	0.095	0.095	0.001	0.003	0.003	0.005	0.103	0.103	0.057	23.831	23.890
Male	0.003	0.130	0.130	0.004	0.011	0.011	0.029	0.167	0.167	0.297	121.446	121.746
Male	0.088	2.541	2.560	0.139	0.400	0.381	0.798	3.480	3.480	12.764	1755.301	1768.430
Male	0.038	1.532	1.540	0.054	0.295	0.292	0.284	2.125	2.125	4.838	1034.202	1039.191
Male	0.005	0.378	0.378	0.005	0.080	0.081	0.027	0.599	0.599	0.375	272.889	273.285
Male	0.018	0.979	0.982	0.035	0.388	0.389	0.212	1.806	1.806	2.898	1028.809	1031.710
Female	0.127	0.414	0.441	0.186	0.185	0.169	1.168	1.460	1.460	29.660	453.510	483.241
Male	0.008	0.518	0.519	0.012	0.213	0.214	0.087	1.007	1.007	0.812	442.595	443.418
Male	0.094	0.453	0.464	0.152	0.104	0.088	0.639	0.763	0.763	8.051	318.148	326.261
Male	0.061	0.351	0.361	0.060	0.136	0.127	0.224	0.537	0.537	3.786	141.444	145.247
Female	0.078	1.557	1.571	0.113	0.491	0.498	0.892	2.770	2.771	10.615	1200.215	1210.908
Male	0.003	0.180	0.180	0.003	0.088	0.088	0.019	0.374	0.374	0.186	127.713	127.901
Male	0.003	0.341	0.341	0.005	0.033	0.033	0.033	0.405	0.405	0.177	250.788	250.971
Male	0.010	1.455	1.458	0.009	0.102	0.102	0.072	1.632	1.632	1.738	1081.594	1083.387
Male	0.007	0.167	0.168	0.011	0.023	0.022	0.067	0.223	0.223	0.632	124.809	125.447
Female	0.018	0.397	0.400	0.031	0.047	0.046	0.182	0.546	0.546	2.277	304.173	306.475
Male	0.003	0.240	0.240	0.002	0.030	0.030	0.014	0.328	0.328	0.232	176.987	177.222
Male	0.023	1.854	1.858	0.032	0.318	0.319	0.207	2.463	2.463	2.861	1392.218	1395.126
Male	0.094	2.543	2.559	0.163	0.560	0.548	1.107	3.903	3.903	11.016	1909.820	1921.741
Female	0.002	0.228	0.228	0.001	0.051	0.051	0.005	0.314	0.314	0.072	170.976	171.051
Male	0.003	0.258	0.258	0.003	0.008	0.008	0.020	0.296	0.296	0.154	191.759	191.916
Male	0.005	0.657	0.658	0.008	0.155	0.155	0.068	1.032	1.032	0.493	490.988	491.486
Male	0.029	0.368	0.372	0.042	0.042	0.034	0.211	0.528	0.528	2.695	273.361	276.123
Male	0.016	0.897	0.900	0.033	0.049	0.047	0.318	1.228	1.228	1.753	648.387	650.317
Male	0.008	0.688	0.689	0.010	0.146	0.146	0.064	1.006	1.006	0.857	494.768	495.663
Male	0.091	2.601	2.618	0.125	0.125	0.113	0.859	3.321	3.321	11.776	1880.643	1892.870
Male	0.002	0.329	0.329	0.001	0.026	0.026	0.010	0.381	0.381	0.114	233.628	233.745
Male	0.193	3.486	3.525	0.217	0.788	0.784	1.224	5.915	5.915	27.174	2505.622	2533.552
Male	0.006	1.560	1.561	0.007	0.116	0.116	0.042	1.779	1.779	0.565	1127.930	1128.504
Female	0.004	0.673	0.673	0.004	0.134	0.134	0.025	0.896	0.896	0.256	507.990	508.249
Female	0.027	1.252	1.257	0.069	0.154	0.154	0.513	1.937	1.937	3.701	970.059	973.835
Female	0.005	0.102	0.102	0.017	0.056	0.056	0.146	0.213	0.213	0.375	75.451	75.836
Female	0.003	0.362	0.363	0.005	0.051	0.051	0.029	0.466	0.466	0.135	256.228	256.366
Female	0.011	1.340	1.341	0.016	0.321	0.320	0.079	1.773	1.773	1.366	1005.974	1007.343
Female	0.006	0.184	0.185	0.016	0.119	0.119	0.146	0.464	0.464	0.492	138.153	138.657
Female	0.013	0.395	0.397	0.024	0.053	0.053	0.153	0.651	0.651	1.248	298.067	299.336
Female	0.008	0.445	0.446	0.011	0.110	0.110	0.059	0.652	0.652	0.617	277.195	277.819
Female	0.018	0.626	0.630	0.028	0.075	0.073	0.214	1.020	1.020	2.808	472.538	475.384
Female	0.002	0.088	0.088	0.001	0.004	0.004	0.003	0.094	0.094	0.057	67.685	67.743
Female	0.006	0.292	0.292	0.009	0.047	0.046	0.046	0.425	0.425	0.457	234.347	234.815
Female	0.078	2.927	2.946	0.088	0.348	0.341	0.588	3.706	3.706	13.390	2139.747	2153.497
Female	0.003	0.095	0.095	0.003	0.017	0.017	0.022	0.115	0.115	0.111	87.847	87.961
Female	0.014	0.544	0.547	0.032	0.202	0.203	0.255	1.050	1.050	1.734	406.576	408.366
Female	0.003	0.079	0.079	0.002	0.020	0.020	0.016	0.105	0.105	0.669	137.835	138.506

Figure 4.3: EDA during baseline

Gender	mean phasic	mean tonic	mean eda	sd phasic	sd tonic	sd eda	max phasic	max tonic	max eda	auc phasic	auc tonic	auc eda
Male	0.013	1.840	1.842	0.026	0.594	0.595	0.198	3.272	3.272	3.065	2374.932	2378.019
Male	0.072	2.681	2.695	0.150	0.442	0.445	0.959	3.947	3.947	18.112	3492.579	3510.829
Female	0.008	0.197	0.198	0.028	0.053	0.055	0.330	0.579	0.641	1.268	385.518	386.825
Male	0.003	0.213	0.213	0.003	0.020	0.020	0.031	0.256	0.256	0.506	417.426	417.936
Female	0.003	0.092	0.092	0.006	0.006	0.007	0.067	0.154	0.154	0.516	154.253	154.770
Male	0.004	0.232	0.233	0.004	0.017	0.018	0.040	0.297	0.306	1.063	464.980	466.052
Male	0.002	0.102	0.102	0.001	0.006	0.006	0.003	0.110	0.110	0.079	93.673	93.754
Male	0.002	0.114	0.114	0.002	0.007	0.007	0.014	0.142	0.142	0.208	102.677	102.887
Male	0.110	4.021	4.046	0.251	0.354	0.329	2.747	4.842	4.842	22.272	3647.347	3669.648
Male	0.016	2.416	2.419	0.026	0.052	0.051	0.254	2.633	2.633	2.189	1543.618	1545.840
Male	0.004	0.303	0.304	0.004	0.026	0.026	0.030	0.342	0.342	0.466	271.191	271.667
Male	0.203	2.702	2.743	0.183	0.301	0.282	1.002	3.382	3.382	30.489	1986.226	2016.953
Female	0.097	0.454	0.477	0.126	0.412	0.409	1.041	1.092	1.092	20.917	420.737	441.706
Male	0.004	0.427	0.427	0.007	0.022	0.022	0.073	0.490	0.490	0.520	397.208	397.729
Male	0.003	0.332	0.333	0.002	0.009	0.009	0.010	0.350	0.350	0.166	221.724	221.895
Male	0.006	0.265	0.266	0.007	0.013	0.012	0.047	0.300	0.300	0.686	254.610	255.302
Female	0.026	1.847	1.851	0.049	0.100	0.099	0.346	2.093	2.093	4.510	1733.932	1738.492
Male	0.002	0.138	0.138	0.001	0.005	0.005	0.005	0.152	0.152	0.126	131.742	131.872
Male	0.003	0.253	0.253	0.005	0.048	0.048	0.032	0.332	0.332	0.254	231.610	231.868
Male	0.007	0.882	0.883	0.007	0.090	0.091	0.043	1.099	1.100	1.067	807.077	808.154
Male	0.002	0.268	0.268	0.001	0.007	0.007	0.007	0.282	0.283	0.140	241.761	241.906
Female	0.004	0.349	0.350	0.007	0.057	0.057	0.056	0.480	0.480	0.466	443.986	444.469
Male	0.002	0.174	0.174	0.001	0.009	0.009	0.006	0.188	0.188	0.156	217.948	218.107
Male	0.031	2.938	2.945	0.058	0.125	0.124	0.567	3.467	3.467	8.737	3804.567	3813.329
Male	0.078	5.171	5.186	0.135	0.278	0.274	0.981	6.220	6.220	18.238	6593.943	6612.707
Female	0.011	0.379	0.381	0.014	0.080	0.080	0.099	0.533	0.533	2.524	484.277	486.817
Male	0.002	0.321	0.321	0.001	0.014	0.014	0.006	0.347	0.347	0.237	441.374	441.614
Male	0.002	0.234	0.234	0.001	0.025	0.025	0.005	0.301	0.301	0.140	193.570	193.712
Male	0.010	0.668	0.669	0.014	0.076	0.076	0.094	0.857	0.857	1.790	913.280	915.077
Male	0.015	1.311	1.314	0.033	0.110	0.110	0.407	1.670	1.670	3.824	1860.051	1863.882
Male	0.004	0.392	0.393	0.008	0.033	0.033	0.092	0.472	0.472	0.448	440.594	441.089
Male	0.016	1.859	1.861	0.040	0.216	0.217	0.325	2.430	2.432	3.431	2555.156	2558.693
Male	0.002	0.364	0.364	0.002	0.014	0.014	0.012	0.393	0.393	0.291	510.246	510.539
Male	0.227	8.720	8.762	0.278	0.789	0.767	1.735	10.438	10.438	57.238	12235.109	12293.046
Male	0.009	1.042	1.043	0.017	0.075	0.076	0.135	1.294	1.294	1.595	1428.606	1430.212
Female	0.014	1.147	1.149	0.041	0.260	0.261	0.414	1.985	1.985	3.101	1640.793	1643.903
Female	0.005	0.454	0.454	0.008	0.146	0.146	0.063	0.749	0.749	0.902	639.862	640.791
Female	0.002	0.169	0.169	0.002	0.020	0.020	0.022	0.232	0.234	0.175	269.965	270.141
Female	0.046	0.274	0.278	0.153	0.181	0.184	1.793	2.438	2.438	7.094	493.889	500.997
Female	0.232	3.565	3.609	0.364	0.798	0.800	2.008	6.147	6.147	81.549	6527.492	6609.288
Female	0.002	0.108	0.108	0.001	0.002	0.002	0.005	0.113	0.113	0.086	124.512	124.599
Female	0.013	0.487	0.489	0.027	0.128	0.129	0.220	0.883	0.883	2.436	683.032	685.483
Female	0.004	0.250	0.251	0.008	0.038	0.039	0.059	0.372	0.374	0.488	346.858	347.362
Female	0.004	0.437	0.437	0.003	0.034	0.034	0.036	0.520	0.522	0.724	596.738	597.472
Female	0.002	0.115	0.115	0.002	0.043	0.043	0.016	0.234	0.234	0.210	157.696	157.908
Female	0.035	0.414	0.418	0.111	0.138	0.140	1.292	1.930	1.930	6.537	729.332	735.914
Female	0.175	4.136	4.177	0.205	0.869	0.869	1.282	5.761	5.761	62.394	6366.187	6428.842
Female	0.006	0.165	0.166	0.007	0.019	0.019	0.044	0.209	0.209	0.889	241.372	242.264
Female	0.090	1.614	1.628	0.132	0.235	0.234	0.818	2.319	2.319	19.920	2354.998	2375.093
Female	0.003	0.123	0.123	0.003	0.006	0.006	0.020	0.147	0.147	0.355	189.313	189.673

Figure 4.4: EDA during negative

4.2 Data Analysis

Table in figure 4.5 shows the descriptive statistics; mean, standard deviation, median, 25th 75th and 95th percentile, of all 10 HRV features during the resting (baseline) phase and during the negative valence phase. Similarly Table in figure 4.6 shows the descriptive statistics; mean, standard deviation, median, 25th 75th and 95th percentile, of all EDA features during the resting (baseline) phase and during the negative valence phase.

	Baseline Session						Negative Valence Session					
	Mean	SD	Median	25th	75th	95th	Mean	SD	Median	25th	75th	95th
SD1	46.897	19.195	44.7	35.25	58.15	82.2	41.7	14.35	42.4	30.65	48.9	64.16
SD2	85.84	29.42	87.1	60.85	107.1	132.2	65.8	22.6	68.8	51	75.3	100
SampEn	2.097	0.53	1.993	1.698	2.523	2.966	1.935	0.558	1.86	1.706	2.312	2.578
DFA(all)	0.8711	0.1539	0.9	0.775	0.984	1.0387	0.743	0.139	0.74	0.685	0.832	0.934
DFA(1)	1	0.262	0.995	0.87	1.224	1.351	0.853	0.189	0.896	0.684	1.004	1.094
DFA(2)	0.8486	0.226	0.876	0.7023	1.0368	1.1418	0.721	0.214	0.72	0.606	0.813	1.041
MeanIBI	782.364	109.40	815.3	731.925	853.925	905.81	803.505	103.25	824.45	741.55	864.35	921.905
SDNN	69.427	22.962	71.5	49	82.625	104.83	55.314	18.47	57.55	40.675	67.925	80.39
MeanHR	78.909	11.947	74.4	70.8	84.425	104.68	76.345	10.676	73.2	69.7	81.175	94.57
SDHR	7.0091	1.829	6.75	5.95	7.875	10.03	5.272	1.588	5.25	4.3	5.95	7.295

Figure 4.5: Statistics for Heart rate variability features calculated during the baseline and Negative valence period

	Baseline Session						Negative Valence Session					
	Mean	**SD**	**Median**	**25th**	**75th**	**95th**	**Mean**	**SD**	**Median**	**25th**	**75th**	**95th**
Mean Phasic	0.03756	0.0481	0.0169	0.00472	0.0574	0.1185	0.03442	0.06089	0.00821	0.00358	0.0234	0.1802
Mean Tonic	0.9125	0.884	0.4334	0.3437	1.4513	2.5424	1.4284	1.992	0.4095	0.277	1.845	4.884
SD Phasic	0.0533	0.0652	0.0315	0.00544	0.06206	0.1798	0.0497	0.0784	0.0144	0.0049	0.0451	0.2339
SD Tonic	0.1832	0.1997	0.1102	0.04025	0.2746	0.54272	0.1409	0.1992	0.05495	0.02045	0.1214	0.54862
Max Phasic	0.3169	0.3932	0.1945	0.0318	0.3481	1.1525	0.3999	0.6428	0.09674	0.03572	0.3916	1.5611
Max Tonic	1.385	1.3857	0.8844	0.4222	1.7992	3.7972	1.7851	2.385	0.5561	0.34424	2.498	5.8758
AUC Phasic	5.062	7.8128	2.01484	0.46633	5.9165	23.572	7.04891	13.1475	1.4315	0.4664	4.3382	28.435
AUC Tonic	686.92	645.16	380.37	237.918	1062.567	1871.19	1662.1	2625.66	464.13	299.77	1828.5	5896.6

Figure 4.6: Statistics for Skin conductance features calculated during the baseline and Negative valence period

Figure 4.7 - 4.14 shows the plots of SD2, DFA and SDNN features of some of the participants calculated from the data collected during both segments. The blue bars represent the values during the baseline and the orange bars represent the values during the emotional stimuli phase (denoted by 'Negative'). Figure 4.7 bar graph plots the values of SD2 (y-axis) for some participants and the box plot in figure 4.8 displays the descriptive statistic of the SD2 values. For almost all the participants, a significant drop during the negative valence phase (orange) can be observed as compared to the baseline. Similar observations can be made from Fig 4.9 to Fig 4.14 of DFA and Standard deviation of IBI respectively. For calculating DFA we require large dataset [61], therefore we were unable to calculate DFA for some of the participants whose IBI data acquired from the sensor was insufficient. Our experiment has suggested that irrespective of the variations in the measures of each participant, SD2, DFA, SDNN, SampEn statistically decreased for all when the participants where shown emotionally evocative pictures and audios with high negative valence.

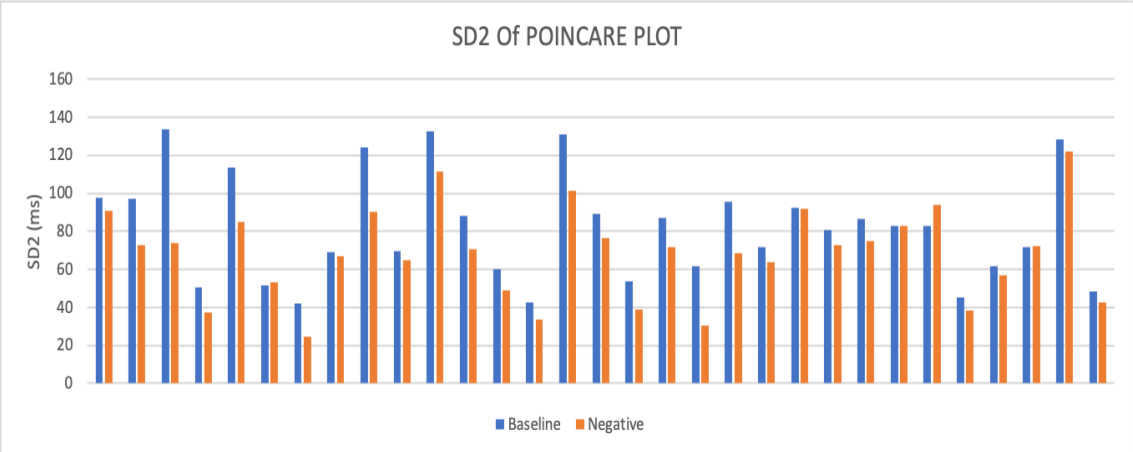


Figure 4.7: Bar graph with the values of SD2 (y-axis) of the participants calculated from the data collected during baseline(blue) and emotional stimuli phase (orange)

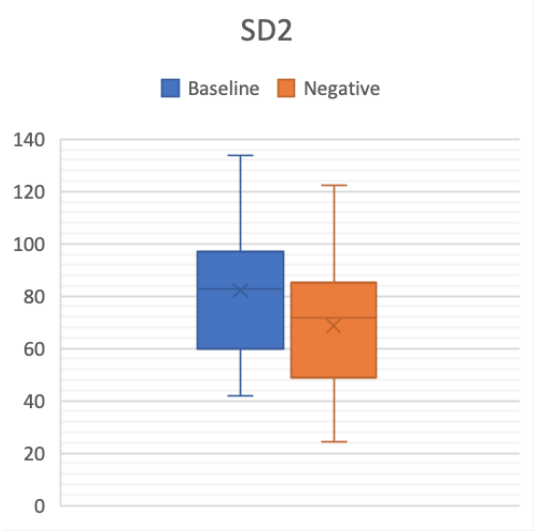


Figure 4.8: box plot displaying the descriptive statistic of the SD2 values of all the participants calculated from the data collected during baseline(blue) and emotional stimuli phase (orange)

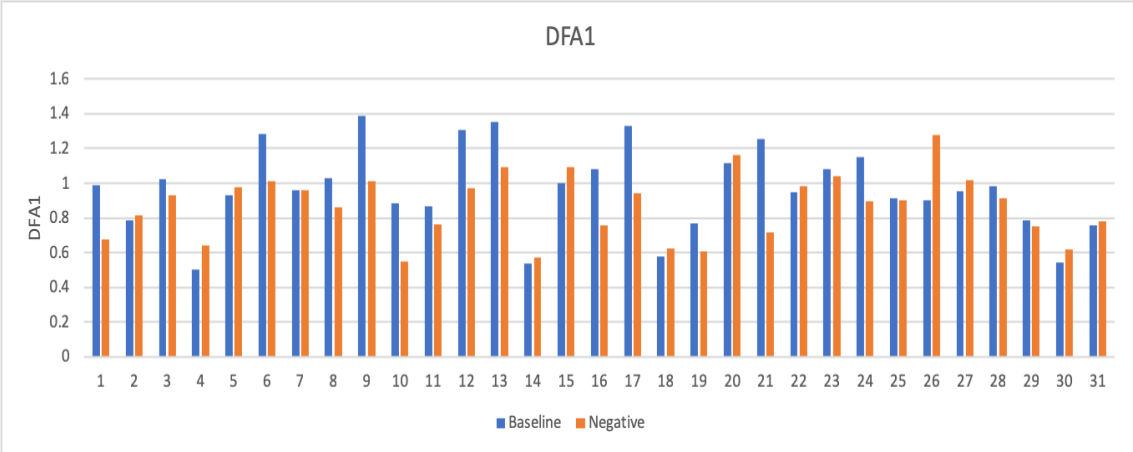


Figure 4.9: Bar graph with the values of DFA1 (y-axis) of the participants calculated from the data collected during baseline(blue) and emotional stimuli phase (orange)

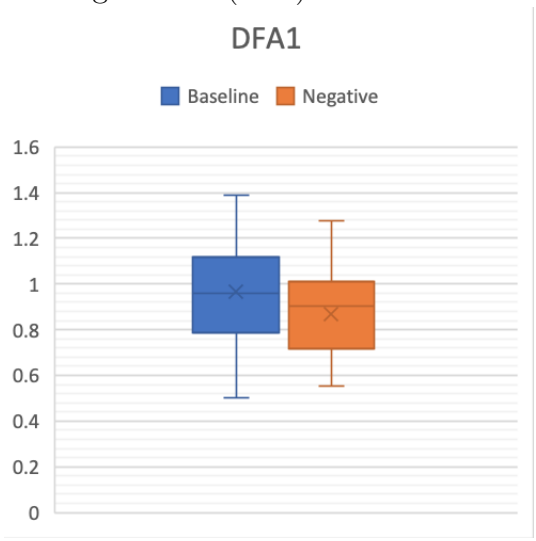


Figure 4.10: box plot displaying the descriptive statistic of the DFA1 values of all the participants calculated from the data collected during baseline(blue) and emotional stimuli phase (orange)

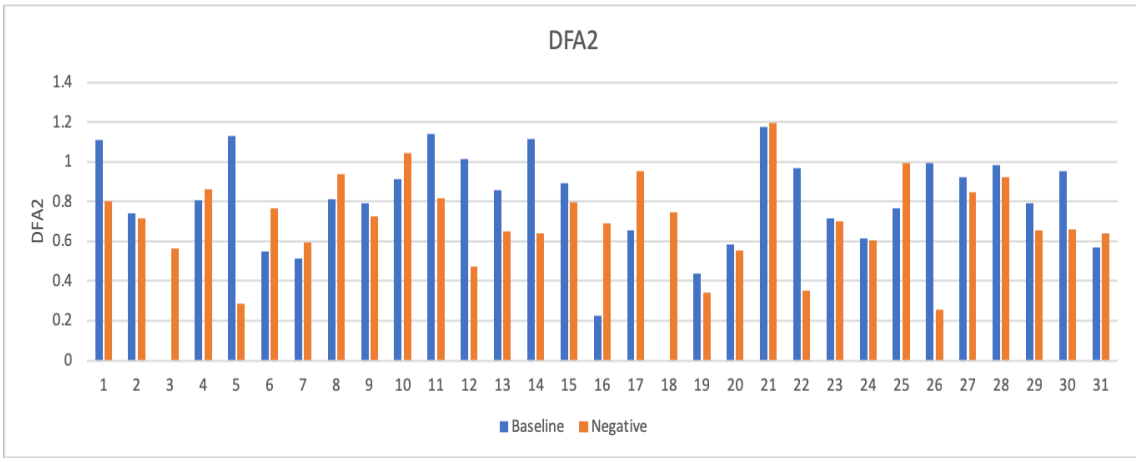


Figure 4.11: Bar graph with the values of DFA2 (y-axis) of the participants calculated from the data collected during baseline(blue) and emotional stimuli phase (orange)

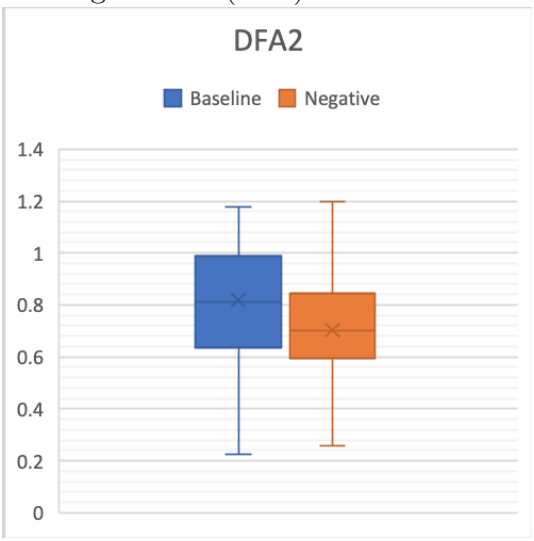


Figure 4.12: box plot displaying the descriptive statistic of the DFA2 values of all the participants calculated from the data collected during baseline(blue) and emotional stimuli phase (orange)

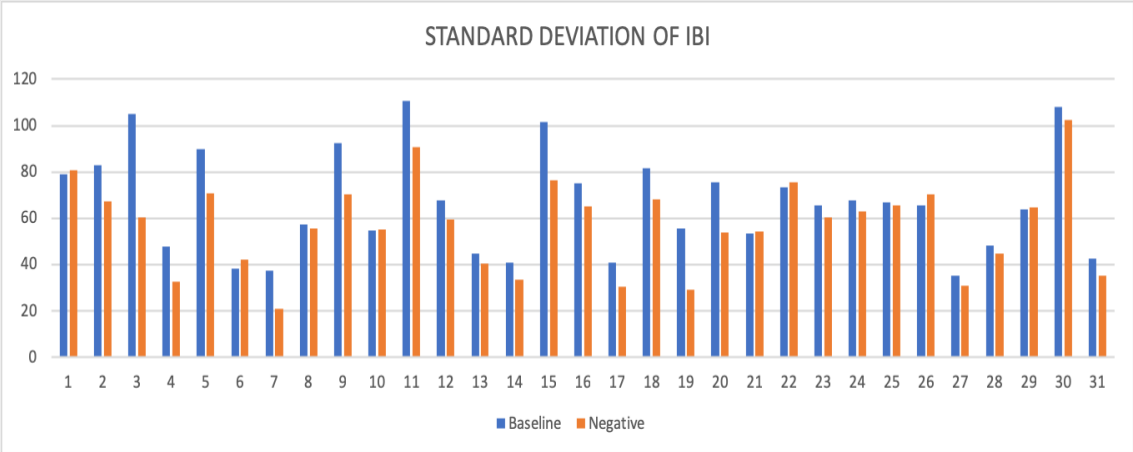


Figure 4.13: Bar graph with the values of SD IBI (y-axis) of the participants calculated from the data collected during baseline(blue) and emotional stimuli phase (orange)

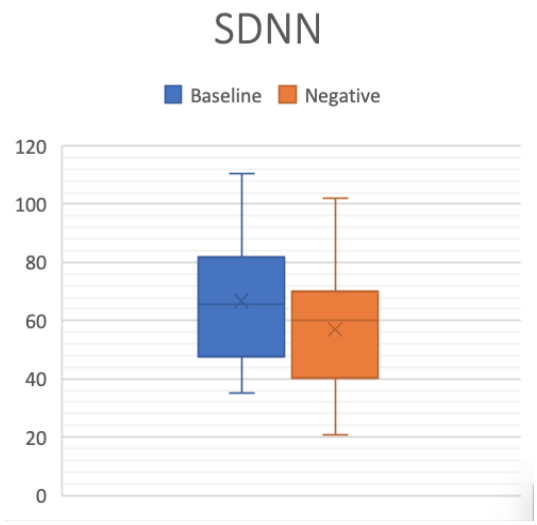


Figure 4.14: box plot displaying the descriptive statistic of the SDNN values of all the participants calculated from the data collected during baseline(blue) and emotional stimuli phase (orange)

4.3 Significance Test

We used Wilcoxon Signed Rank test to calculate the significance, the reason being that it does not make the assumption that the dependent variable should be normally distributed. Figure 4.15 below shows the results of the Wilcoxon Signed Rank between the Heart rate variability features acquired from the baseline period and the negative valence period. Based on the test it was observed that there was a significant difference between the variables SD2, DFA, MEANIBI, SDNN, MEANHR and SDHR between the two groups (baseline and Negative).

Similarly, Figure 4.16 below shows the results of the Wilcoxon Signed Rank between the electrodermal activity features acquired from the baseline period and the negative valence period. Based on the test it was observed that there was a significant difference between the variables auc tonic and auc eda between the two groups (baseline and Negative).

Test Statistics[a]

	SD1_N - SD1	SD2_N - SD2	SAMPEN_N - SAMPEN	DFA_ALL_N - DFA_ALL
Z	-1.666[b]	-4.409[b]	-.292[c]	-2.757[b]
Asymp. Sig. (2-tailed)	.096	.000	.770	.006

Test Statistics[a]

	DFA1_N - DFA_1	DFA2_N - DFA2	MEANIBI_N - MEANIBI	SDNN_N - SDNN
Z	-2.205[b]	-1.654[b]	-2.724[c]	-4.106[b]
Asymp. Sig. (2-tailed)	.027	.098	.006	.000

Test Statistics[a]

	MEANHR_N - MEANHR	SDHR_N - SDHR
Z	-2.754[b]	-4.773[b]
Asymp. Sig. (2-tailed)	.006	.000

a. Wilcoxon Signed Ranks Test

b. Based on positive ranks.

c. Based on negative ranks.

Figure 4.15: Wilcoxon signed rank results between the Heart Rate Variability features calculated from the baseline and the negative valence period data.

Test Statistics[a]

	mean_phasic_n - mean_phasic	mean_tonic_n - mean_tonic	mean_eda_n - mean_eda	sd_phasic_n - sd_phasic
Z	-1.308[b]	-1.482[c]	-1.462[c]	-.690[b]
Asymp. Sig. (2-tailed)	.191	.138	.144	.490

Test Statistics[a]

	sd_tonic_n - sd_tonic	sd_eda_n - sd_eda	max_phasic_n - max_phasic	max_tonic_n - max_tonic
Z	-.845[b]	-.864[b]	-.410[c]	-1.231[c]
Asymp. Sig. (2-tailed)	.398	.388	.682	.218

Test Statistics[a]

	max_eda_n - max_eda	auc_phasic_n - auc_phasic	auc_tonic_n - auc_tonic	auc_eda_n - auc_eda
Z	-1.240[c]	-.796[c]	-4.803[c]	-4.793[c]
Asymp. Sig. (2-tailed)	.215	.426	.000	.000

a. Wilcoxon Signed Ranks Test

b. Based on positive ranks.

c. Based on negative ranks.

Figure 4.16: Wilcoxon signed rank results between the skin conductance features calculated from the baseline and the negative valence period data.

4.4 Gender Difference

Many studies have reported possible gender difference in physiological responses [23]. To observe if there is any obvious difference in the physiological responses of male and female participants in our study we divided the data into two clusters, female and male, and analyzed and compared their data during the negative valence phase. We did not observe any pattern between the physiological responses of male and female participants from the data collected in this study. The number of male and female participants might be one of the factors. The plots in the figure 4.17 below shows the SD2, DFA1, DFA2 during negative valence phase: Male (blue) Vs Female (gray) participants.

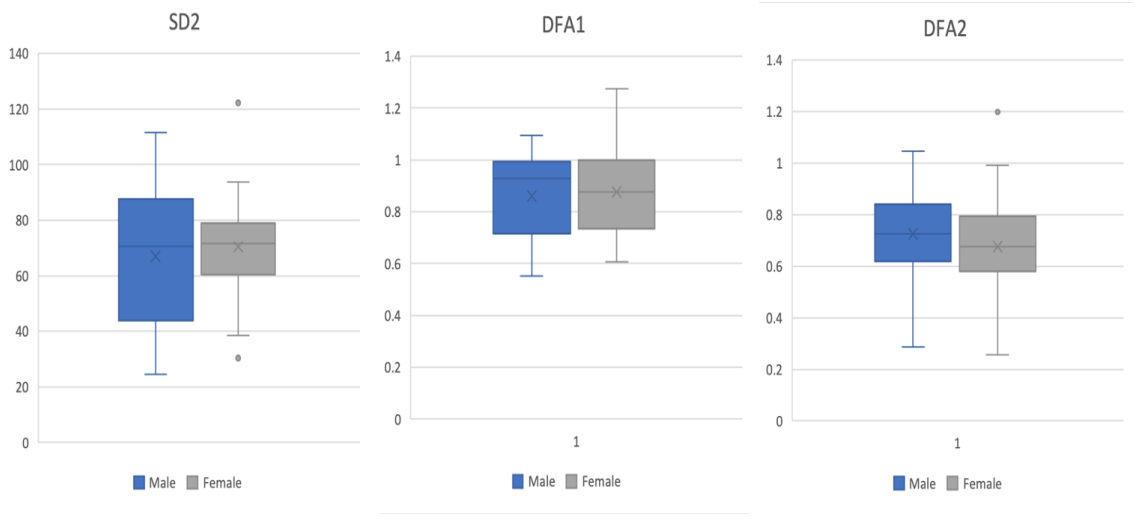


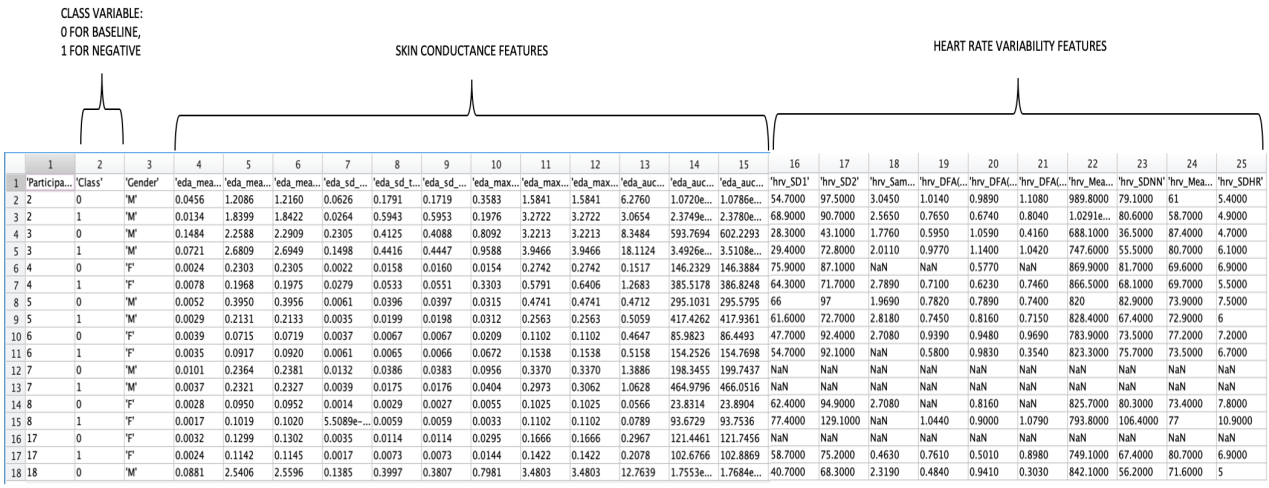
Figure 4.17: box plot displaying the descriptive statistic of SD2, DFA1, DFA2 during negative valence phase: Male (blue) Vs Female (gray) participants

4.5 Data set

From the data gathered we were able to create a predictive model for negative emotion. The data gathered from all 50 participants during baseline and negative valence phase was labeled to create a database for supervised learning. The column 'class' is the dependent variable with two classes, 0 and 1. 0 refers to baseline, which is the normal condition. 1 refers to the emotional arousal phase, which is the negative emotion condition. Following are the independent variable:

- Gender
- Mean Phasic
- Mean Tonic
- Mean Eda
- STD Phasic
- STD Tonic
- STD Eda
- Max Phasic
- Max Tonic
- Max Eda
- AUC Phasic
- AUC Tonic
- AUC Eda
- Poincare SD1
- Poincare SD2
- HRV SampEn
- DFA(all)
- DFA(1)
- DFA(2)
- Mean IBI
- SDNN
- Mean HR
- SD HR

With 1 dependent variable, 23 independent variable and total number of 50 participants and two data collection scenrios , the total size of the database was 100 rows (50 participants X 2 Phases) and 24 columns (refer to the table in figure 4.17 below).



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
1	'Participa...	'Class'	'Gender'	'eda_mea...	'eda_mea...	'eda_mea...	'eda_sd_...	'eda_sd_t...	'eda_sd_...	'eda_max...	'eda_max...	'eda_max...	'eda_auc...	'eda_auc...	'eda_auc...	'hrv_SD1'	'hrv_SD2'	'hrv_Sam...	'hrv_DFA(...	'hrv_DFA(...	'hrv_DFA(...	'hrv_Mea...	'hrv_SDNN'	'hrv_Mea...	'hrv_SDHR'
2	2	0	'M'	0.0456	1.2086	1.2160	0.0626	0.1791	0.1719	0.3583	1.5841	1.5841	6.2760	1.0720e...	1.0786e...	54.7000	97.5000	3.0450	1.0140	0.9890	1.1080	989.8000	79.1000	61	5.4000
3	2	1	'M'	0.0134	1.8399	1.8422	0.0264	0.5943	0.5953	0.1976	3.2722	3.2722	3.0654	2.3749e...	2.3780e...	68.9000	90.7000	2.5650	0.7650	0.6740	0.8040	1.0291e...	80.6000	58.7000	4.9000
4	3	0	'M'	0.1484	2.2588	2.2909	0.2305	0.4125	0.4088	0.8092	3.2213	3.2213	8.3484	593.7694	602.2293	28.3000	43.1000	1.7760	0.5950	1.0590	0.4160	688.1000	36.5000	87.4000	4.7000
5	3	1	'M'	0.0721	2.6809	2.6949	0.1498	0.4416	0.4447	0.9588	3.9466	3.9466	18.1124	3.4926e...	3.5108e...	29.4000	72.8000	2.0110	0.9770	1.1400	1.0420	747.6000	55.5000	80.7000	6.1000
6	4	0	'F'	0.0024	0.2303	0.2305	0.0022	0.0158	0.0160	0.0154	0.2742	0.2742	0.1517	146.2329	146.3884	75.9000	87.1000	NaN	NaN	0.5770	NaN	869.9000	81.7000	69.6000	6.9000
7	4	1	'F'	0.0078	0.1968	0.1975	0.0279	0.0533	0.0551	0.3303	0.5791	0.6406	1.2683	385.5178	386.8248	64.3000	71.7000	2.7890	0.7100	0.6230	0.7460	866.5000	68.1000	69.7000	5.5000
8	5	0	'M'	0.0052	0.3950	0.3956	0.0061	0.0396	0.0397	0.0315	0.4741	0.4741	0.4712	295.1031	295.5795	66	97	1.9690	0.7820	0.7890	0.7400	820	82.9000	73.9000	7.5000
9	5	1	'M'	0.0029	0.2131	0.2133	0.0035	0.0199	0.0198	0.0312	0.2563	0.2563	0.5059	417.4262	417.9361	61.6000	72.7000	2.8180	0.7450	0.8160	0.7150	828.4000	67.4000	72.9000	6
10	6	0	'F'	0.0039	0.0715	0.0719	0.0037	0.0067	0.0067	0.0209	0.1102	0.1102	0.4647	85.9823	86.4493	47.7000	92.4000	2.7080	0.9390	0.9480	0.9690	783.9000	73.5000	77.2000	7.2000
11	6	1	'F'	0.0035	0.0917	0.0920	0.0061	0.0065	0.0066	0.0672	0.1538	0.1538	0.5158	154.2526	154.7698	54.7000	92.1000	NaN	0.5800	0.9830	0.3540	823.3000	75.7000	73.5000	6.7000
12	7	0	'M'	0.0101	0.2364	0.2381	0.0132	0.0386	0.0383	0.0956	0.3370	0.3370	1.3886	198.3455	199.7437	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
13	7	1	'M'	0.0037	0.2321	0.2327	0.0039	0.0175	0.0176	0.0404	0.2973	0.3062	1.0628	464.9796	466.0516	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
14	8	0	'F'	0.0028	0.0950	0.0952	0.0014	0.0029	0.0027	0.0055	0.1025	0.1025	0.0566	23.8314	23.8904	62.4000	94.9000	2.7080	NaN	0.8160	NaN	825.7000	80.3000	73.4000	7.8000
15	8	1	'F'	0.0017	0.1019	0.1020	5.5089e-...	0.0059	0.0059	0.0033	0.1102	0.1102	0.0789	93.6729	93.7536	77.4000	129.1000	NaN	1.0440	0.9000	1.0790	793.8000	106.4000	77	10.9000
16	17	0	'F'	0.0032	0.1299	0.1302	0.0035	0.0114	0.0114	0.0295	0.1666	0.1666	0.2967	121.4461	121.7456	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
17	17	1	'F'	0.0024	0.1142	0.1145	0.0017	0.0073	0.0073	0.0144	0.1422	0.1422	0.2078	102.6766	102.8869	58.7000	75.2000	0.4630	0.7610	0.5010	0.8980	749.1000	67.4000	80.7000	6.9000
18	18	0	'M'	0.0881	2.5406	2.5596	0.1385	0.3997	0.3807	0.7981	3.4803	3.4803	12.7639	1.7553e...	1.7684e...	40.7000	68.3000	2.3190	0.4840	0.9410	0.3030	842.1000	56.2000	71.6000	5

Figure 4.18: Emotional stimuli database for supervised Learning

4.6 Predictive model

We trained machine learning models for the following three classification algorithms:

- Support Vector Machine (SVM)
- Discriminant Anaylsis
- Binary decision tree

The data set was split into, 2/3 for training and 1/3 for testing. The subsets of training and testing was randomly selected from the dataset of 100 instances. The SVM model, Discriminant analysis and Binary decision tree models were build on the training data and then the models were used to make predictions on the test set. Figure 4.18 below shows a flow of the process.

Since the data for training and testing was selected randomly, the models would give a different prediction accuracy each time it is executed. Therefore, we used K-fold validation, with k=10. In each iteration we split the data set into training and testing sets and use the training set to train the three models and testing set to test the models. We then evaluate the models performance based on an error metric to determine the accuracy of the models. We repeat the process 10 times with different subsets of train and test data. The validation results (accuracy) of each model are then averaged to give an estimate of the model's predictive performance. Table below shows the average accuracy of each model, with the highest and the lowest obtained accuracy among the 10 iterations.

	SVM	Discriminant Anaylsis	Binary decision tree
Average accuracy	73.0%	68.3%	52.3%
Lowest obtained	60.0%	56.7%	23.3%
Highest obtained	86.0%	80.0%	66.7%

Table 4.1: Machine learning models and their performances

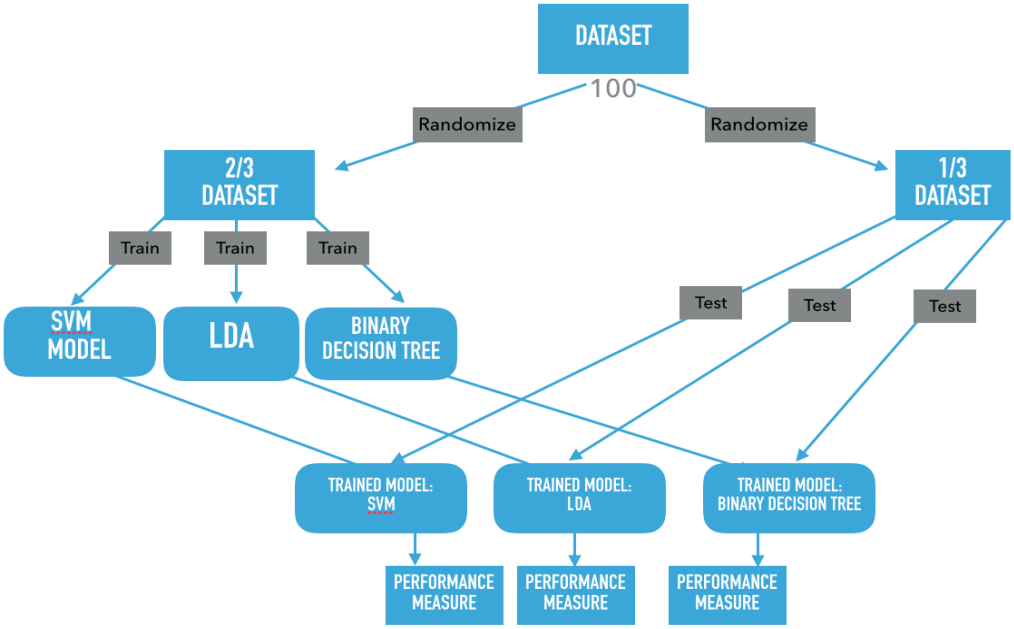


Figure 4.19: Dataset splitting for machine learning models

4.7 Survey Results

During the experiment the participants were asked to fill out the survey with rating scale for each image and sound to give an estimate of how pleasant and excited the participants found the images and audios to be. The rating scale as shown in Figure 3. was based on self-Assessment Manikin (SAM: Bradley & Lang, 1994) [8][9], with a graphical scale of 1-9 for pleasant and for excitement. The top panel rates the Valence, the more it is on the right the negative the valence. The bottom panel rates the excitement, the more it is towards the left the higher the excitement. The images and audios picked for the study had the highest negative valence of the total IAPS and IADS dataset. Pleasure and arousal are the main measure for emotional study [9], hence we focused on only these two dimensions.

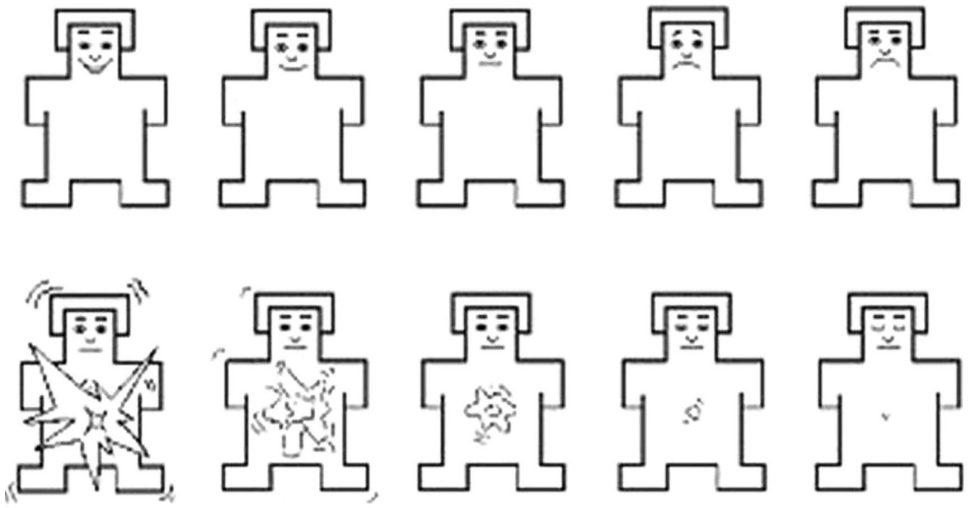


Figure 4.20: SAM rating scale

To analyze the ratings of all the participants we developed a scoring scheme. Both the scales are numbered one to nine from left to right, one being the left most and nine being the right most. Therefore, for pleasant, 9 being the most unpleasant and 1 being the most pleasant. And for excitement, 1 being the most excited and 9 being the calmest. Therefore, we can drive three ranges 1-3 for low, 4-6 for medium, 7-9 for high. Table 4.2. below shows the statistics of the ratings of all the participants for all the images and audios. All the participants rated the images and audios on average 7.2 for valence and 4.6 for excitement. Therefore, according to our scoring scheme, on average they found the images and audios to be highly unpleasant (negative valence), with medium excitement.

	Mean	**SD**
Pleasant	7.2	0.9
excitement	4.6	0.8

Table 4.2: Survey outcome

After the experiment, we also had the chance to get verbal feedback from some of the participants about their reactions to the negative emotional stimuli part of the study. The general response was that due to the relative ease of access to such visual media, they did not feel as startled or uncomfortable as would have been otherwise. Almost 4 out of 5 people agreed with this feedback. One of them said "I feel bad that I didn't feel bad while watching the negative pictures, the society has made us that way". Taking these feedback into consideration our results might have shown a more significant decrease in magnitude of the features discussed above, if the participants were not as desensitized to such media.

5 Conclusions

This thesis covers:

- Proposed design of a objective decision support system for bipolar episodes.
- Design of a emotional stimuli study to investigate physiological responses (HRV and EDA) with respect to psychological changes
- Feature extraction of HRV and EDA data
- Analysis of HRV and EDA features during resting (baseline) and negative valence (emotional stimuli) phase
- Machine learning models build using the gathered dataset.

We investigated the ability of Electrodermal activity and Heart Rate Variability to identify the activity of the autonomic nervous system in response to emotional stimuli. According to the results of our study following features of HRV and EDA indicated potential to be used as an indicator of emotional and mental state: SD2, SampEn, DFA, Mean IBI, Mean HR, SDNN, SDHR, AUC Tonic. The effect of emotional stimuli on skin conductance and the variation between the baseline and negative valence readings greatly depended on the individual, some people showed low tolerance towards the negative media resulting in high phasic peaks and overall higher skin conductance level as compared to their baseline. Meanwhile, many other showed little to no significant change in their electrodermal activity, which can be explained

by the survey outcomes discussed in the previous section on how open access to media has made people, especially youngsters who are most exposed, desensitized to negative images and audios. Irrespective of the limitation of the intensity of the stimulus that we used for our experiment, Electrodermal activity and heart rate variability showed potential to track emotional change. Further investigations with larger amount of data, with more diverse participants and long-term analysis of HRV can supplement establishment of this claim. Moreover, observing the significant difference between the baseline readings of all individuals and the difference in their physiological responses to the emotional stimuli, it might be a better approach to build personalized model to track and identify emotional change using a model trained on the data specific to the person.

The data collection in our preliminary study involved two sensor modalities, Heart Rate Variability (HRV) and Electrodermal Activity (EDA). HRV and EDA Data was collected for baseline and negative valence phase. Using the data gathered we created a labeled dataset to train machine learning models to identify negative valence emotion. We used three different supervised machine learning techniques, Support vector machine (SVM), binary decision tree and Linear discriminant analysis (LDA). SVM as compared to others outperformed with an average accuracy of 73%. Binary decision tree performance was the poorest with an average accuracy of 68%. Our study, though conducted on healthy individuals, showed promising results for a predictive model based on physiological signals to identify emotional dysregulation.

With the advancement of technologies focus of researchers has been largely shifted towards objective monitoring and prediction of the bipolar state. Figure 3 shows the evolution of these technologies that aid bipolar disorder and help patients self-manage the disorder. HRV, EDA, sleep, activity and acoustic voice are some of the biomarker on which researches has been done and has shown promising results.

Using a combination of these biomarkers to diversify and aim for a better accuracy for prediction is also an approach taken by some researchers [18][34] .

Though there are numerous researches on assistive and predictive technologies for bipolar disorder, and they have evolved substantially over time with advancement of mobile, wireless and sensor technologies (figure 3), however there are many challenges before such systems can be deployed and made available for patients and clinics to use.

With the seriousness of the disorder across the globe and a dire need of a system to objectively identify a patient's bipolar state, researches are demonstrating promising results that can potentially address current gap between the diagnosis and treatment.

Our study, though conducted on healthy individuals, showed computation and analysis of the features and predictive model building based on combination of physiological signals to identify emotional dysregulation.

5.1 Strengths and Limitations

The total number of participants whose data we collected and analyzed were 50 in total which is a considerable size for a pilot study. With 21 female and 29 male participants we were able to maintain a somewhat gender balance as well. Moreover, we collected the data from two different sensor modality (HRV and EDA), which diversified the approach. The strength of the study mainly lies in the 23 features from two sensor modalities from 50 participants that we collected, and the analysis and results we obtained from it.

According to the IRB approved for this study participants were well informed of the audios and images with negative valence. Hence, the negative valence media was foreseen by all the participants which might have affected the results. Secondly, we

had a limitation on the negative valence content that we used in the study. The negative valence images were only taken from the International Affective picture system, and many participants gave a feedback that they did not find the media to be very unpleasant, which might affect the physiological responses that we gathered from them. Moreover, having access to only healthy participants and no bipolar patients was another limitation of this study.

5.2 Future Work

The next step towards this research study is to conduct it on bipolar patients. The data from the participants in this study could serve as a control population. Secondly, reaching out to the stakeholders and taking their input on the design idea of the proposed system might help improve it to be a better fit for the patients.

Secondly, on a bigger picture the main focus of research in the current decade is towards personalized monitoring systems as discussed in the previous sections. Such systems come under the category of Body Area Network (BAN), as it consists of sensors signaling physiological data from the patient [29]. An amalgamation of such a network with a smart mobile phone is the next generation of healthcare applications. Although with innumerable technological advances there are still many challenges to tackle before such systems can be deployed and practically made available.

The first and the foremost challenge is to attain power efficiency. Devices in the system should consume less power so that battery recharging is as less often as possible. Wireless communication, such as using Bluetooth, consumes a lot of power hence low power operation is the biggest challenge [29] and needs to be addressed before a system can be deployed and made available for users. Future work and progress in the research on size reduction of the devices, security and privacy will

enhance the feasibility and applicability of similar aforementioned systems [29] [55]. Along with technical challenges there are also ethical and clinical dilemmas of using mobile devices that are related to data confidentiality and network security that would need to be addressed [13].

A Appendix A

A.1 Streaming Data

This is the main ViewController.m file of the IOS mobile application that connects to the sensor via bluetooth, streams data and inserts it into the MySQL database.

```
1
2
3  #import "ViewController.h"
4  #import "SecondViewController.h"
5
6
7  NSString * myDB;
8  NSInteger bvp_count=0;
9  NSString *txtName = @"hi";
10
11 @implementation ViewController
12 @synthesize sno,status_label,ble_label;
13
14
15 -(void)prepareForSegue:(UIStoryboardSegue *)segue sender:(id)sender{
16
17     if ([[segue identifier] isEqualToString:@"goSeg"]) {
18         SecondViewController *svc;
19         svc = [segue destinationViewController];
20         svc.pNum = sno.text;
```

```
21
22          //----------------------------------
23          //prepare url to pass
24          NSString *strURL = [NSString stringWithFormat:@"http
                ://131.212.129.93:8888/insert_participant.php?pno=%@",sno.
                text];
25
26          //execute php code
27          NSData *dataURL = [NSData dataWithContentsOfURL:[NSURL
                URLWithString:strURL] ];
28
29          //to recieve the returned value
30          NSString *strResult = [[[NSString alloc]initWithData:dataURL
                encoding:NSUTF8StringEncoding] autorelease];
31
32          NSLog(@"%@",strResult);
33          //----------------------------------
34      }
35
36  /*
37      if ([[segue identifier] isEqualToString:@"doneSeg"]) {
38          ViewController *vc;
39          vc = [segue destinationViewController];
40      }
41  */
42  }
43
44  - (IBAction)scanForDevicesAndConnectPressed:(id)sender {
45      [EmpaticaAPI discoverDevicesWithDelegate:self];
46  }
47
```

```
48 - (void)didDiscoverDevices:(NSArray *)devices {
49     if (devices.count > 0) {
50         // Print names of available devices
51         for (EmpaticaDeviceManager *device in devices) {
52             NSLog(@"Device: %@", device.name);
53         }
54 
55         // Connect to first available device
56         EmpaticaDeviceManager *firstDevice = [devices objectAtIndex:0];
57         [firstDevice connectWithDeviceDelegate:self];
58     } else {
59         NSLog(@"No device found in range");
60         ble_label.text = @"No device found in range";
61     }
62 }
63 
64 - (void)didUpdateBLEStatus:(BLEStatus)status {
65     switch (status) {
66         case kBLEStatusNotAvailable:
67             NSLog(@"Bluetooth low energy not available");
68             //ble_label.text = @"Bluetooth low energy not available";
69             break;
70         case kBLEStatusReady:
71             NSLog(@"Bluetooth low energy ready");
72             //ble_label.text = @"Bluetooth low energy ready";
73             break;
74         case kBLEStatusScanning:
75             NSLog(@"Bluetooth low energy scanning for devices");
76             //ble_label.text = @"Bluetooth low energy scanning for
                devices";
77             break;
```

```
78          default:
79              break;
80      }
81  }
82
83  - (void)didUpdateDeviceStatus:(DeviceStatus)status forDevice:(
        EmpaticaDeviceManager *)device {
84      switch (status) {
85          case kDeviceStatusDisconnected:
86              NSLog(@"Device Disconnected");
87              //status_label.text=@"Device status: Device Disconnected";
88              break;
89          case kDeviceStatusConnecting:
90              NSLog(@"Device Connecting");
91              //status_label.text=@"Device status: Device Connecting";
92              break;
93          case kDeviceStatusConnected:
94              NSLog(@"Device Connected");
95              //status_label.text=@"Device status: Device Connected";
96              break;
97          case kDeviceStatusDisconnecting:
98              NSLog(@"Device Disconnecting");
99              //status_label.text=@"Device status: Device Disconnecting";
100             break;
101         default:
102             break;
103     }
104 }
105
106 - (void)didReceiveAccelerationX:(char)x y:(char)y z:(char)z
        withTimestamp:(double)timestamp fromDevice:(EmpaticaDeviceManager *)
```

```
    device {
107 //    NSLog(@"Acceleration (x,y,z) received: (%d,%d,%d) at timestamp %f
        ", x, y, z, timestamp);
108 }
109
110 - (void)didReceiveBatteryLevel:(float)level withTimestamp:(double)
        timestamp fromDevice:(EmpaticaDeviceManager *)device {
111 //    NSLog(@"Battery level received: %.2f at timestamp %f", level,
        timestamp);
112 }
113
114 - (void)didReceiveBVP:(float)bvp withTimestamp:(double)timestamp
        fromDevice:(EmpaticaDeviceManager *)device {
115     //NSLog(@"BVP received: %f at timestamp %f", bvp, timestamp);
116     bvp_count=bvp_count+1;
117     if (bvp_count==10) {
118         //---------------------------------
119         //this piece of code prepares a url with the ibi to pass to a
                php file, which inserts that ibi in the mysql database
120         //prepare url to pass
121
122         NSString *bvpstrURL = [NSString stringWithFormat:@"http
                ://131.212.129.93:8888/insert_bvp.php?ts=%f&bvp=%f",
                timestamp,bvp];
123
124         //execute php code
125         NSData *bvpdataURL = [NSData dataWithContentsOfURL:[NSURL
                URLWithString:bvpstrURL] ];
126
127         //to recieve the returned value
128         NSString *bvpstrResult = [[[NSString alloc]initWithData:
```

```
            bvpdataURL encoding:NSUTF8StringEncoding] autorelease];
129
130         NSLog(@"%@",bvpstrResult);
131         //------------------------------------
132         bvp_count=0;
133     }
134
135 }
136
137 - (void)didReceiveGSR:(float)gsr withTimestamp:(double)timestamp
    fromDevice:(EmpaticaDeviceManager *)device {
138     NSLog(@"GSR received: %f at timestamp %f", gsr, timestamp);
139
140     //Galvanic Skin Response
141
142     //------------------------------
143     //this piece of code prepares a url with the gsr to pass to a php
            file, which inserts that gsr
144     //in the mysql database
145     //prepare url to pass
146     NSString *gsrstrURL = [NSString stringWithFormat:@"http
            ://131.212.129.93:8888/insert_gsr.php?ts=%f&gsr=%f",timestamp,
            gsr];
147
148     //execute php code
149     NSData *gsrdataURL = [NSData dataWithContentsOfURL:[NSURL
            URLWithString:gsrstrURL] ];
150
151     //to recieve the returned value
152     NSString *gsrstrResult = [[[NSString alloc]initWithData:gsrdataURL
            encoding:NSUTF8StringEncoding] autorelease];
```

```
153
154     NSLog(@"%@",gsrstrResult);
155
156     //----------------------------------
157
158
159 }
160
161 - (void)didReceiveIBI:(float)ibi withTimestamp:(double)timestamp
        fromDevice:(EmpaticaDeviceManager *)device {
162     NSLog(@"IBI received: %f at timestamp %f", ibi, timestamp);
163 //This method is invoked when a new interbeat interval (IBI) value is
        available
164     //Inter beat interval
165
166     //----------------------------------
167     //this piece of code prepares a url with the ibi to pass to a php
            file, which inserts that ibi in the mysql database
168     //prepare url to pass
169     NSString *ibistrURL = [NSString stringWithFormat:@"http
            ://131.212.129.93:8888/insert_ibi.php?ts=%f&ibi=%f",timestamp,
            ibi];
170
171     //execute php code
172     NSData *ibidataURL = [NSData dataWithContentsOfURL:[NSURL
            URLWithString:ibistrURL] ];
173
174     //to recieve the returned value
175     NSString *ibistrResult = [[[NSString alloc]initWithData:ibidataURL
            encoding:NSUTF8StringEncoding] autorelease];
176
```

```
177     NSLog(@"%@",ibistrResult);
178     //------------------------------------
179
180 }
181
182 - (void)didReceiveTemperature:(float)temp withTimestamp:(double)
        timestamp fromDevice:(EmpaticaDeviceManager *)device {
183     NSLog(@"Temperature received: %.2f at timestamp %f", temp, timestamp)
            ;
184 }
185
186 -(void)didReceiveTagAtTimestamp:(double)timestamp fromDevice:(
        EmpaticaDeviceManager *)device{
187     NSLog(@"Tag received at timestamp %f", timestamp);
188 }
189
190
191
192
193 -(IBAction)insert:(id)sender
194 {
195  //this is a test button for connection to the database
196     //----------------------select-----------------------------------
197     //prepare url to pass
198     NSString *strURL = [NSString stringWithFormat:@"http
            ://131.212.129.93:8888/service.php?name=%s","shukar"];
199
200     //execute php code
201     NSData *dataURL = [NSData dataWithContentsOfURL:[NSURL URLWithString
            :strURL] ];
202
```

```
203     //to recieve the returned value
204     NSString *strResult = [[[NSString alloc]initWithData:dataURL
            encoding:NSUTF8StringEncoding] autorelease];
205
206     NSLog(@"%@",strResult);
207
208     //------------------------insert-----------------------------------
209     NSURL *strfile = [NSURL fileURLWithPath:@"file://Users/yumnaanwar/
            Desktop/test/"];
210     NSString *filecontent = [NSString stringWithContentsOfURL:strfile
            encoding:NSUTF8StringEncoding error:Nil];
211     NSLog(@"%@",filecontent);
212     NSString *output =[NSString stringWithFormat:@"%s","shukar"];
213     [output writeToURL:strfile atomically:YES encoding:
            NSUTF8StringEncoding error:Nil];
214
215 }
216
217     -(void)dealloc
218     {
219         [txtName release];
220         [sno release];
221         [status_label release];
222         [ble_label release];
223         [super dealloc];
224     }
225 - (IBAction)submit:(id)sender {
226 }
227 @end
```

A.2 EDA features

This python code would take the EDA data, the Phasic(scr) data, drive the tonic values from it and calculate the Mean, Max, Standard deviation and area under the curve.

```
1
2  import pandas as pd
3
4  import statistics
5  import csv
6  eda=[]
7
8  #CHANGE PATH HERE
9  with open("//Users//yumnaanwar//Desktop//Thesis_Yumna//prompting_Study//
       eda//E4_DATA//1//eda_only//EDA_10.csv") as f:
10     reader = csv.reader(f)
11     for row in reader:
12         eda.append(float(' '.join(row)))
13         #print(' '.join(row) )
14
15
16 print(len(eda))
17
18 #sampling based on average. so its sample size is 4, then each 4
       instances are averaged
19 eda_samp=[]
20 c=0
21 avg=0
22 for i in range(0,len(eda)):
23     avg=avg+float(eda[i])
```

```
24      c=c+1
25      if c==4:
26          eda_samp.append(float(avg)/4)
27          c=0
28          avg=0
29
30  #sampling based on time. so its sample size is 4, then each instance is
        increased by 0.25
31  eda_samp_time=[]
32  c=0
33  for i in range(0,len(eda)):
34      eda_samp_time.append(c)
35      c=c+0.25
36
37
38  #CHANGE PATH HERE
39  scr = pd.ExcelFile("/Users//yumnaanwar//Desktop//Thesis_Yumna//
        prompting_Study//eda//E4_DATA//1//eda_only//EDA_10_scrlist.xls")
40  sheetX = scr.parse(1)
41  var1= sheetX["CDA.SCR-Onset"]
42  var2 = sheetX["CDA.SCR-Amplitude"]
43
44  var1_int=[]
45  var1_f=[]
46  scr=[]
47  for i in var2:
48      scr.append(i)
49  for i in var1:
50      var1_int.append(int(round(i)))
51      var1_f.append(float(i))
52
```

```
53
54
55 # In[777]:
56
57
58 print(len(eda_samp))
59 print(len(eda_samp_time))
60 print(len(eda))
61 print(len(var1_int))
62 print(len(var1_f))
63 print(len(scr))
64
65
66 # In[778]:
67
68
69 #based on 0.25 step size
70 tonic=[]
71 p_count=0
72 for i in range(0,len(eda)):
73
74     #to avoid index out of range
75     #the scr list is small. of size 231 and the tonic list is large with
           1292 size.
76     if p_count <len(scr):
77
78         #if the onset is equal to the index of the eda time then
              subtract phasic from eda to get tonic.
79         if eda_samp_time[i]==var1_f[p_count]:
80             tonic.append(float(eda[i])-float(scr[p_count]))
81             p_count=p_count+1
```

```
82          #if no value is found that means phasic is zero.
83          else:
84              tonic.append(float(eda[i]))
85
86      else:
87          tonic.append(float(eda[i]))
88
89  print(p_count)
90  print(len(tonic))
91  #print(tonic)
92
93
94
95  # In[779]:
96
97
98  count=0
99  #Checking your results
100 for i in range(0,len(eda)):
101     # print(str(float(eda[i])-float(tonic[i])))
102     if((float(eda[i])-float(tonic[i]))>0):
103         count=count+1
104 print(count)
105
106
107
108 # In[780]:
109
110
111 #tonic
112 #scr
```

```
#eda
import numpy as np
from numpy import trapz

mean_phasic=statistics.mean(scr)
mean_tonic=statistics.mean(tonic)
mean_eda=statistics.mean(eda)

sd_phasic=statistics.stdev(scr)
sd_tonic=statistics.stdev(tonic)
sd_eda=statistics.stdev(eda)

max_phasic=max(scr)
max_tonic=max(tonic)
max_eda=max(eda)

auc_phasic=np.trapz(scr)
auc_tonic=np.trapz(tonic)
auc_eda=np.trapz(eda)


print("Mean Phasic: " + str(mean_phasic))
print("Mean Tonic: " + str(mean_tonic))
print("Mean EDA: " + str(mean_eda))

print("SD Phasic: " + str(sd_phasic))
print("SD Tonic: " + str(sd_tonic))
print("SD EDA: " + str(sd_eda))

print("max Phasic: " + str(max_phasic))
print("max Tonic: " + str(max_tonic))
```

```
144 print("max EDA: " + str(max_eda))
145
146 print("AUC Phasic: " + str(auc_phasic))
147 print("AUC Tonic: " + str(auc_tonic))
148 print("AUC eda: " + str(auc_eda))
149
150 with open('/Users//yumnaanwar//Desktop//Thesis_Yumna//prompting_Study//
    eda//E4_DATA//eda.csv', mode='a',newline='') as file:
151     file_writer = csv.writer(file, delimiter=',', quotechar='"', quoting
        =csv.QUOTE_MINIMAL)
152     #file_writer.writerow(['Participant','phase','mean_phasic','
        mean_tonic','mean_eda','sd_phasic','sd_tonic','sd_eda','
        max_phasic','max_tonic','max_eda','auc_phasic','auc_tonic','
        auc_eda'])
153     file_writer.writerow([])
154     #CHANGE PATH HERE
155     file_writer.writerow(['45','neg',mean_phasic,mean_tonic,mean_eda,
        sd_phasic,sd_tonic,sd_eda,max_phasic,max_tonic,max_eda,
        auc_phasic,auc_tonic,auc_eda])
156
157
158 #write tonic to file
159 #CHANGE PATH HERE
160 with open('/Users//yumnaanwar//Desktop//Thesis_Yumna//prompting_Study//
    eda//E4_DATA//1//eda_only//tonic_10.csv', mode='w') as file:
161     file_writer = csv.writer(file, delimiter=',', quotechar='"', quoting
        =csv.QUOTE_MINIMAL)
162     file_writer.writerow(['tonic'])
163     for i in range (0,len(tonic)):
164         file_writer.writerow([tonic[i]])
```

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